AN AUTOMATIC SYSTEM TO DETECT EQUIVALENCE BETWEEN ITERATIVE ALGORITHMS

SHIPU ZHAO∗, LAURENT LESSARD†, AND MADELEINE UDELL∗

Abstract. When are two algorithms the same? How can we be sure a recently proposed algorithm is novel, and not a minor twist on an existing method? In this paper, we present a framework for reasoning about equivalence between a broad class of iterative algorithms, with a focus on algorithms designed for convex optimization. We propose several notions of what it means for two algorithms to be equivalent, and provide computationally tractable means to detect equivalence. Our main definition, oracle equivalence, states that two algorithms are equivalent if they result in the same sequence of calls to the function oracles (for suitable initialization). Borrowing from control theory, we use state-space realizations to represent algorithms and characterize algorithm equivalence via transfer functions. Our framework can also identify and characterize some algorithm transformations including permutations of the update equations, repetition of the iteration, and conjugation of some of the function oracles in the algorithm. To support the paper, we have developed a software package named LINNAEUS that implements the framework to identify other iterative algorithms that are equivalent to an input algorithm. More broadly, this framework and software advances the goal of making mathematics searchable.

Key words. optimization algorithm, algorithm equivalence, algorithm transformation.

1. Introduction. Large-scale optimization problems in machine learning, signal processing, and imaging have fueled ongoing interest in iterative optimization algorithms. New optimization algorithms are regularly proposed in order to capture more complicated models, reduce computational burdens, or obtain stronger performance and convergence guarantees.

However, the novelty of an algorithm can be difficult to establish because algorithms can be written in different equivalent forms. For example, algorithm 1.1 was originally proposed by Popov [35] in the context of online optimization. Algorithm 1.2 is a reformulation of algorithm 1.1 adapted for use in generative adversarial networks (GANs) [21]. Algorithm 1.3 is an adaptation of Optimistic Mirror Descent [36] used by Daskalakis et al. [13] and also used to train GANs. Finally, algorithm 1.4 was proposed by Malitsky [29] for solving monotone variational inequality problems. (Some of these algorithms were originally proposed in conjunction with projections or other operations that make them more distinct.) In all four algorithms, the vectors $x_1^k$ and $x_2^k$ are algorithm states, $\eta$ is a tunable parameter, and $F^k(\cdot)$ is the gradient of the loss function at time step $k$.

\begin{align*}
\text{Algorithm 1.1 (Modified Arrow–Hurwicz)} \\
& \text{for } k = 1, 2, \ldots \text{ do} \\
& \quad x_1^{k+1} = x_1^k - \eta F^k(x_2^k) \\
& \quad x_2^{k+1} = x_2^{k+1} - \eta F^k(x_2^k) \\
& \text{end for}
\end{align*}

\begin{align*}
\text{Algorithm 1.3 (Optimistic Mirror Descent)} \\
& \text{for } k = 1, 2, \ldots \text{ do} \\
& \quad x_2^{k+1} = x_2^k - \eta F^k(x_2^k) + \eta F^{k-1}(x_2^{k-1}) \\
& \text{end for}
\end{align*}

\begin{align*}
\text{Algorithm 1.2 (Extrapolation from the past)} \\
& \text{for } k = 1, 2, \ldots \text{ do} \\
& \quad x_2^k = x_1^k - \eta F^{k-1}(x_2^{k-1}) \\
& \quad x_1^{k+1} = x_1^k - \eta F^k(x_2^k) \\
& \text{end for}
\end{align*}

\begin{align*}
\text{Algorithm 1.4 (Reflected Gradient Method)} \\
& \text{for } k = 1, 2, \ldots \text{ do} \\
& \quad x_2^{k+1} = x_1^k - \eta F^k(2x_1^k - x_2^{k-1}) \\
& \text{end for}
\end{align*}

Algorithms 1.1 to 1.4 are equivalent in the sense that when suitably initialized, the sequences $(x_1^k)_{k \geq 0}$ and $(x_2^k)_{k \geq 0}$ are identical for all four algorithms.† Although these particular equivalences are not difficult to verify and many have been explicitly pointed out in the literature, for example in [21], algorithm equivalence is not always immediately apparent.

One famous example concerns the relations between the Chambolle-Pock method, Douglas-Rachford splitting, and the alternating directions method of multipliers (ADMM): indeed, showing the connection

---

* Cornell University (sz533@cornell.edu, udell@cornell.edu).
† Northeastern University (l.lessard@northeastern.edu).

† In their original formulations, algorithms 1.1, 1.2, and 1.4 included projections onto convex constraint sets. We assume an unconstrained setting here for illustrative purposes. Some of the equivalences no longer hold in the constrained case.
between Chambolle-Pock and Douglas-Rachford requires a full page of mathematics in [11]. In contrast, our analysis supports a single coherent view of these algorithms that can be summarized in a commutative diagram (figure 7).

In this paper, we present a framework for reasoning about algorithm equivalence, with the ultimate goal of making the analysis and design of algorithms more principled and streamlined. This includes:

- A universal way of representing algorithms, inspired by methods from control theory.
- Several definitions of what it means for algorithms to be equivalent.
- A computationally efficient way to verify whether two algorithms are equivalent.

Briefly, our method is to parse each algorithm to a standard form as a linear system in feedback with a nonlinearity; to compute the transfer function of each linear system; and to check, using a computer algebra system, if there are parameter values that make the transfer functions equal.

We must point out a tension in our terminology: the notion of algorithm equivalence we define below is rather broad, which is in order to discover interesting connections between algorithms. As a consequence, equivalent algorithms (in our terminology) can nevertheless be extremely useful for different tasks: for example, writing one algorithm in different ways can yield different generalizations, different interpretations, different computational complexity, and different numerical stability. On the other hand, equivalent algorithms will share many properties, such as convergence, stability, and fixed points.

We also present a software package implementing this framework named LINNAEUS\footnote{Named after Carl Linnaeus, a botanist and zoologist who invented the modern system of naming organisms.}, for the classification and taxonomy of iterative algorithms. The software is a search engine, where the input is an algorithm described using natural syntax, and the output is a canonical form for the algorithm along with any known names and pointers to relevant literature. The approach described in this paper allows LINNAEUS to search over first-order optimization algorithms such as gradient descent with acceleration, ADMM, and the extra-gradient method. As the database in LINNAEUS grows, it will help algorithm researchers understand and efficiently discover connections between algorithms. More generally, LINNAEUS advances the goal of making mathematics searchable.

This paper is organized as follows. In section 2, we briefly summarize existing literature related to our work. In section 3, we introduce three examples of equivalent algorithms that motivate our framework. In section 4, we briefly review important background on linear systems and optimization used throughout the paper. We formally define two notions of algorithm equivalence, oracle equivalence and shift equivalence, in section 5 and discuss how to characterize them via transfer functions in sections 6 and 7. Certain transformations can also be identified and characterized with our framework including algorithm repetition, repeating an algorithm multiple times, and conjugation, a transformation using conjugate function oracles. These are discussed in sections 8 and 9 respectively. In section 10, we briefly introduce our software package LINNAEUS for the classification of iterative algorithms.

2. Related work. A variety of existing work advances the goal of making mathematics searchable. This work is too diverse to survey here. As an example, consider the On-Line Encyclopedia of Integer Sequences: given a sub-sequence or a keyword, the encyclopedia will find a matching sequence and return useful information such as mathematical motivation for the sequence and links to other literature [41]. As a very different example, recent work in deep learning has led to new language models, such as GPT3, that can generate code snippets, including machine learning models, javascript applications, and SQL queries [1, 2, 8, 39]. As these models are trained from large corpuses of data, we might view such models as implementing a generalized search.

Within the optimization literature, several standard forms have been proposed to represent problems and algorithms. For example, the CVX* modeling languages represent (disciplined) convex optimization problems in a standard conic form, building up the representations of complex problems from a few basic functions and a small set of composition rules [14, 23, 24, 40, 44]. This paper builds on a foundation developed by Lessard et al. [27] that represents first-order algorithms as linear systems in feedback with a nonlinearity. Lessard et al. use this representation to analyze convergence properties of an algorithm with integral quadratic constraints. Our work extends theirs with the insight that such representations can be computed automatically by a computer.

There are rich connections between many first-order methods for convex optimization. These algorithms are surveyed in a recent textbook by Ryu and Yin, which summarizes and unifies several operator splitting...
methods for convex optimization [38]. Many of these connections are well known to experts, but the connections have traditionally been complex to explain, communicate, or even remember. For example, Boyd et al. [6] write, “There are also a number of other algorithms distinct from but inspired by ADMM. For instance, Fukushima [20] applies ADMM to a dual problem formulation, yielding a ‘dual ADMM’ algorithm, which is shown in [18] to be equivalent to the ‘primal Douglas-Rachford’ method discussed in [16, §3.5.6].”

As another example, Chambolle and Pock in [11] propose a new primal-dual splitting algorithm and demonstrate that transformations of their algorithm can yield Douglas-Rachford splitting and ADMM, using a full page of mathematics to sketch the connection. Using our framework, the (many!) relations between the Chambolle-Pock method, Douglas-Rachford splitting, and ADMM can be established precisely and conveyed efficiently in a commutative diagram; see section 9 and figure 7 in particular.

3. Motivating examples. To explain what we mean by algorithm equivalence, we introduce three motivating examples in this section. Each provides a different view of how two algorithms might be equivalent.

Algorithm 3.1

\[
\begin{align*}
\text{for } k = 0, 1, 2, \ldots & \text{ do} \\
x_1^{k+1} &= 2x_1^k - x_2^k - \frac{1}{10} \nabla f(2x_1^k - x_2^k) \\
x_2^{k+1} &= x_1^k \\
\text{end for}
\end{align*}
\]

The first example consists of algorithms 3.1 and 3.2. These algorithms are equivalent in a strong sense: when suitably initialized, we may transform the iterates of algorithm 3.1 by the invertible linear map \( \xi_1^k = 2x_1^k - x_2^k, \xi_2^k = -x_1^k + x_2^k \) to yield the iterates of algorithm 3.2. We say that the sequences \((x_1^k)_{k \geq 0}\) and \((x_2^k)_{k \geq 0}\) are equivalent to sequences \((\xi_1^k)_{k \geq 0}\) and \((\xi_2^k)_{k \geq 0}\) up to an invertible linear transformation.

Algorithm 3.2

\[
\begin{align*}
\text{for } k = 0, 1, 2, \ldots & \text{ do} \\
\xi_1^{k+1} &= \xi_1^k - \xi_2^k - \frac{1}{5} \nabla f(\xi_1^k) \\
\xi_2^{k+1} &= \xi_2^k + \frac{1}{5} \nabla f(\xi_1^k) \\
\text{end for}
\end{align*}
\]

The second example consists of algorithms 3.3 and 3.4. These algorithms do not even have the same number of state variables, so these algorithms are not equivalent up to an invertible linear transformation. But when suitably initialized, we may transform the iterates of algorithm 3.3 by the linear map \( \xi^k = -x_1^k + 2x_2^k \) to yield the iterates of algorithm 3.4. This transformation is linear but not invertible. Instead, notice that the sequence of calls to the gradient oracle are identical: the algorithms satisfy oracle equivalence, a notion we will define formally later in this paper.

Algorithm 3.3

\[
\begin{align*}
\text{for } k = 0, 1, 2, \ldots & \text{ do} \\
x_1^{k+1} &= 3x_1^k - 2x_2^k + \frac{1}{5} \nabla f(-x_1^k + 2x_2^k) \\
x_2^{k+1} &= x_1^k \\
\text{end for}
\end{align*}
\]

Algorithm 3.4

\[
\begin{align*}
\text{for } k = 0, 1, 2, \ldots & \text{ do} \\
\xi^{k+1} &= \xi_k - \frac{1}{5} \nabla f(\xi_k) \\
\text{end for}
\end{align*}
\]

The third example consists of algorithms 3.5 and 3.6. With suitable initialization, they will generate the same sequence of calls to the proximal operator, ignoring the very first call to one of the oracles. Specifically, algorithm 3.6 is initialized as \( \xi_1^0 = x_1^0, \xi_2^0 = x_2^1 \) and the first call to \( \text{prox}_f \) in algorithm 3.5 is ignored. We will say they are equivalent up to a prefix or shift: they satisfy shift equivalence.

Generalizing from these motivating examples, we will call algorithms equivalent when they generate an identical sequence (e.g., of states or oracle calls) up to some transformations, with suitable initialization. To make our ideas formal, we need a few definitions and some ideas from control theory. We will then revisit those motivating examples and define algorithm equivalence.
4. Preliminaries. We let $\mathbb{R}^n$ denote the standard Euclidean space of $n$-dimensional vectors, and use boldface lowercase symbols denote semi-infinite sequences of vectors, which we index using superscripts. For example, we may write $x := (x^0, x^1, \ldots)$, where $x^k \in \mathbb{R}^n$ for each $k \geq 0$. Subscripts index components or subvectors: for example, we may write $x = [z^1_2] \in \mathbb{R}^n$, where $x_1 \in \mathbb{R}^{n_1}$ and $x_2 \in \mathbb{R}^{n-n_1}$.

4.1. Optimization. 

 Optimization problem, objective, and constraints. An optimization problem is identified by an objective function and a constraint set. The objective may be written as the sum of several functions, and the constraint set may be the intersection of several sets. As an example, in the optimization problem (4.1) [6]

\[
\begin{align*}
\text{minimize} & \quad f(x) + g(z) \\
\text{subject to} & \quad Ax + Bz = c,
\end{align*}
\]

the objective function is $f(x) + g(z)$ and the constraint set is $\{(x, z) : Ax + Bz = c\}$.

 Oracles. We assume an oracle model of optimization: we can only access an optimization problem by querying oracles at discrete query points [7, §4; 9, §1; 32, §1]. Oracles might include the gradient or proximal operator of a function, or projection onto a constraint set [4, §6; 19, §2; 34, §1]. Each query to the oracle returns an output such as the function value, gradient, or proximal operator. For example, the oracles for problem (4.1) might include the gradients or proximal operators of $f$ and $g$, and projection onto the hyperplane $\{(x, z) : Ax + Bz = c\}$.

4.2. Algorithms. Detecting equivalence between any pair of algorithms is beyond the scope of this paper. Instead, we restrict our attention to equivalence between iterative linear time-invariant optimization algorithms. In the following section, we provide some intuition and define each of these terms. Further formalism of these terms will be provided in the next subsection on control theory.

 Iterative algorithms. Given an optimization problem and an initial point $x^0 \in X$, an iterative algorithm $A$ generates a sequence of points $x := (x^k)_{k \geq 0}$ by repeated application of the map $A : X \to X$. (We do not distinguish the algorithm from its associated map.) Hence, $x^{k+1} = A(x^k)$ for $k \geq 0$. We call $x^k$ the state of the algorithm at time $k$. We make two important simplifying assumptions when treating algorithms.

 First, suppose the operator $A$ calls each different oracle exactly once. (We will see how to extend our ideas to more complex algorithms later.) This assumption forbids trivial repetition, such as $A' := A \circ A$. Second, we consider algorithms that are time-invariant. In general, one could envision an algorithm $A^k$ that changes at each timestep. Such time-varying algorithms are common in practice: for example, gradient-based methods with diminishing stepsizes. We view time-varying algorithms as a scheme for switching between different time-invariant algorithms. Since our aim is to reason about algorithm equivalence, we restrict our attention to time-invariant algorithms. A nice benefit of this restriction is that we can define algorithm equivalence independently of the choice of initial point.

The formulation $x^{k+1} = A(x^k)$ is general enough to include algorithms with multiple timesteps. For example consider algorithm 1.4: $x^{k+1}_1 = x^k_1 - \eta F(2x^k_1 - x^{k-1}_1)$. If we define the new state $x^{k+1}_2 := x^{k-1}_1$ and let $x^k := [x^k_1 \ x^k_2]$, then we may rewrite the algorithm as

\[
\begin{align*}
x^{k+1} &= \begin{bmatrix} x^{k+1}_1 \\ x^{k+1}_2 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x^k_1 \\ x^k_2 \end{bmatrix} - \eta \begin{bmatrix} 2 & -1 \end{bmatrix} \begin{bmatrix} x^k_1 \\ x^k_2 \end{bmatrix} \\
&= A \left( \begin{bmatrix} x^k_1 \\ x^k_2 \end{bmatrix} \right) = A(x^k).
\end{align*}
\]

The algorithm $A$ contains a combination of oracle calls and state updates. Define $y^k$ and $u^k$ to be the input and output of the oracles called at time $k$, respectively. Now, write three separate equations for the state update, oracle input, and oracle output. Applying this to (4.2), we obtain:

\[
\begin{align*}
\begin{bmatrix} x^{k+1}_1 \\ x^{k+1}_2 \end{bmatrix} &= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x^k_1 \\ x^k_2 \end{bmatrix} + \begin{bmatrix} -\eta \\ 0 \end{bmatrix} u^k \quad (\text{state update}), \\
y^k &= \begin{bmatrix} 2 & -1 \end{bmatrix} \begin{bmatrix} x^k_1 \\ x^k_2 \end{bmatrix} \quad (\text{oracle input}), \\
u^k &= F(y^k) \quad (\text{oracle output}).
\end{align*}
\]

 Oracle sequence. We have defined an algorithm $A$ as a map $X \to X$. In optimization, it is also conventional to write an algorithm as a sequence of update equations, that are executed sequentially on a computer.
to implement the map. When this sequence of updates is executed, we may record the sequence of states or the sequence of oracle calls (oracle and its input pairs), which we call the oracle sequence. There may be several ways of writing the algorithm as a sequence of updates, which may produce different state sequences or oracle sequences. We are not aware of any practical algorithm for optimization that may be written to produce two different oracle sequences. Hence we will assume for now that the oracle sequence produced by an algorithm is unique. 3 We will revisit this assumption later in the paper (section 7) to see how our ideas extend to more complex (not-yet-discovered) algorithms.

**Linear algorithms.** The equations (4.3) have the general linear form

\[(4.4a)\] \[x^{k+1} = Ax^k + Bu^k,\]
\[(4.4b)\] \[y^k = Cx^k + Du^k,\]
\[(4.4c)\] \[u^k = \phi(y^k).\]

We say that a time-invariant algorithm is linear if it can be written in the form of (4.4), where \(x^k\) is the algorithm state and \(\phi\) is the set of oracles. Here \(\phi\) can be any nonlinear map, including a map with internal state. For example, the oracle \(\phi\) corresponding to the subgradient \(\partial f\) of a non-differentiable function \(f\) might make a choice to ensure the output is unique and consistent, for example, by selecting the subgradient of minimum norm; the oracle \(\phi\) corresponding to a stochastic gradient might include an internal random seed that ensures the output is unique and deterministic, given the seed.

In the rest of the paper, unless specifically noted, our discussion is limited to linear algorithms. We will see that the class of linear algorithms includes commonly used algorithms, such as accelerated methods, proximal methods, operator splitting methods, and more [25, 27].

The general form (4.4) represents a convenient parameterization of linear algorithms in terms of matrices \((A, B, C, D)\), but it is only a starting point. For example, algorithms 1.1 to 1.4 have different \((A, B, C, D)\) parameters despite being equivalent algorithms. In the next section, we show how tools from control theory can be brought to bear on these sorts of representations.

**Remark.** For an arbitrary state-space realization \((A, B, C, D)\), the corresponding algorithmic sequence may not exist or may not be unique. However, any implementable practical algorithm, written as a sequence of update equations, has a corresponding algorithmic sequence that exists and is unique: it is obtained by performing the steps indicated in the update equations and recording the values of \(x, u, \) and \(y\).

### 4.3. Control theory.

This subsection provides a brief overview of relevant methods and terminology from control theory. More detail can be found in standard references such as [3, Ch. 1–3] and [48, Ch. 1,2,5].

**Algorithms as linear systems.** Let \(u\) denote the entire sequence of \(u^k\) and \(y\) denote the entire sequence of \(y^k\). The equations in (4.4) can be separated into two parts. Equations (4.4a) and (4.4b) define a map \(H\) from \(u\) to \(y\) compactly as \(y = Hu\), while (4.4c) defines a map \(\Phi\) from \(y\) to \(u\) as \(u = \Phi y\), where \(\Phi = \text{diag}\{\phi, \phi, \ldots\}\). We can represent these algebraic relations visually via the block-diagram shown in figure 1.

Consider map \(H\) defined by (4.4a) and (4.4b). For simplicity, we assume that \(x^0 = 0\). As we eliminate \(\{x^1, \ldots, x^k\}\) from (4.4a) and (4.4b), map \(H\) can be represented as a semi-infinite matrix,

---

3This assumption eliminates the possibility that some oracles may be permuted without changing the state sequence: e.g.,

**Algorithm 4.1**

| for \(k = 1, 2, \ldots\) do |
|---|
| \[x_1^{k+1} = A_1(x_1^k)\] |
| \[x_2^{k+1} = A_2(x_2^k)\] |
| \[x_3^{k+1} = A_3(x_1^{k+1}, x_2^{k+1})\] |
| end for |

**Algorithm 4.2**

| for \(k = 1, 2, \ldots\) do |
|---|
| \[x_1^{k+1} = A_1(x_1^k)\] |
| \[x_2^{k+1} = A_2(x_2^k)\] |
| \[x_3^{k+1} = A_3(x_1^{k+1}, x_2^{k+1})\] |
| end for |

Here, the algorithm may be equally well written with the oracle sequence \((A_1, A_2, A_3)\) as with the oracle sequence \((A_2, A_1, A_3)\). But again, we are not aware of any concrete examples of optimization algorithms with this structure.
In control theory, map $H$ is considered as a (discrete-time) system that maps a sequence of inputs $u$ to a sequence of outputs $y$. Map $H$ is linear since it can be represented as a semi-infinite matrix. The matrix representation is lower-triangular and it indicates $H$ is causal. Further, $H$ is time-invariant because the matrix representation is (block) Toeplitz, which means that $H$ is (block) constant along diagonals from top-left to bottom right. Thus, $H$ is a causal linear time-invariant system. For the rest of this paper, we will work with such systems and we will refer to such systems as linear systems.

Further, to combine maps $H$ and $\Phi$ together, a linear algorithm in the form of (4.4) can be regarded as a linear system connected in feedback with a nonlinearity shown by figure 1. At time $k$, $u^k$ is the input and $y^k$ is the output of the system. Nonlinear feedback $\phi$ represents the set of oracles such as the gradient or subgradient of a convex function and it maps the output $y^k$ to the input $u^k$.

State-space realization. Reconsider equations (4.4a) and (4.4b). They correspond to the state-space realization of system $H$. In control theory, a state-space realization is characterized by an internal sequence of states $x$ that evolves according to a difference equation with parameters $(A,B,C,D)$:

\begin{equation}
\begin{aligned}
x^{k+1} &= Ax^k + Bu^k, \\
y^k &= Cx^k + Du^k,
\end{aligned}
\end{equation}

or equivalently, 
\[
\begin{bmatrix}
x^{k+1} \\
y^k
\end{bmatrix} = L \begin{bmatrix}
x^k \\
u^k
\end{bmatrix}, \quad \text{where } L = \begin{bmatrix} A & B \\ C & D \end{bmatrix}.
\]

Here, $u^k \in \mathbb{R}^m$, $y^k \in \mathbb{R}^p$, and $x^k \in \mathbb{R}^n$. The parameters $(A,B,C,D)$ are matrices of compatible dimensions, so $A \in \mathbb{R}^{n \times n}$, $B \in \mathbb{R}^{n \times m}$, $C \in \mathbb{R}^{p \times n}$, and $D \in \mathbb{R}^{p \times m}$. The state-space realization corresponding to the system $H$ can also be characterized by omitting all vectors and writing the block matrix $L$ shown in (4.6) (right), which is the map from $(x^k, u^k)$ to $(x^{k+1}, y^k)$.

In this paper, we rely on such formalism that represents algorithms as linear systems using a state-space realization as (4.6) for each algorithm, following [25, 27]. The state-space realization $L$ represents the linear part of an algorithm and map $\phi$ represents the nonlinear part. Moreover, we have $A = (L, \phi)$. In this way, we can unroll figure 1 in time to obtain the block-diagram shown in figure 2. Each dashed box in figure 2 represents map $A$ for each iteration.

Impulse response and transfer function. From (4.5), without the assumption that $x^0 = 0$, we can obtain

\begin{equation}
y^k = CA^k x^0 + \sum_{j=0}^{k-1} C(A)^{k-(j+1)} Bu^j + Du^k.
\end{equation}
The output $y^k$ is the sum of $C(A)^k x^0$, which is due to the initial condition $x^0$, and $\sum_{j=0}^{k-1} C(A)^{k-j-1} Bu^j + Du^k$, which is due to the inputs $\{u^0, \ldots, u^k\}$. The compact form $y = Hu$ and its matrix representation (4.5) omit the first term that depends on $x^0$. These representations are formally equivalent to the state-space model only when the state is initialized at $x^0 = 0$. However, linearity of $H$ allows the two contributions to be studied separately:

$$\text{(total response)} = \underbrace{\text{(zero input response)}}_{\text{set } u^k = 0 \text{ for } k \geq 0} + \underbrace{\text{(zero state response)}}_{\text{set } x^0 = 0}.$$

This decomposition is analogous to writing the general solution to a linear differential (or difference) equation as the sum of a homogeneous solution (due to initial conditions only) and a particular solution (due to the non-homogeneous terms only). We will characterize linear systems by their input-output map. The input-output map depends only on the zero state response, which allows us to avoid details about initialization. For simplicity, we denote the entries in the matrix representation of $H$ in (4.5) as

$$H^k = \begin{cases} D & k = 0 \\ C(A)^{k-1}B & k \geq 1 \end{cases}.$$  

(4.8)

To study the zero state response, recall from (4.5) that

$$y^k = H^k u^0 + H^{k-1} u^1 + \cdots + H^1 u^{k-1} + H^0 u^k.$$

(4.9)

The sequence $(H^k)_{k \geq 0}$ is called the impulse response of $H$, because it corresponds to the impulsive input $u^0 = 1$ and $u^j = 0$ for $j \geq 1$.

A convenient way to represent $H$ is via the use of a transfer function. To this end, we can represent $y$ and $u$ as generating functions in the variable $z^{-1}$. Equating powers of $z^{-1}$, we have:

$$\begin{align*}
\underbrace{(y^0 + y^1 z^{-1} + y^2 z^{-2} + \cdots)}_{\hat{y}(z)} &= \left(\underbrace{H^0 + H^1 z^{-1} + H^2 z^{-2} + \cdots}_{R(z)}\right) \underbrace{(u^0 + u^1 z^{-1} + u^2 z^{-2} + \cdots)}_{\hat{u}(z)}.
\end{align*}$$

(4.10)

We can recover (4.9) by expanding the multiplication in (4.10) and grouping terms with the same power of $z^{-1}$. So when written as generating functions, the output is related to the input via multiplication. The functions $\hat{y}$ and $\hat{u}$ are the $z$-transforms of the sequences $y$ and $u$, respectively, and $H$ is called the transfer function. If $p \geq 2$ or $m \geq 2$ (the $H^k$ are matrices), then $H$ is called the transfer matrix.

Substituting (4.8) into the definition of the transfer function, we can write a compact form for the formal power series $\hat{H}$, which converges on some appropriate set:

$$\hat{H}(z) = \begin{bmatrix} A & B \\ C & D \end{bmatrix} = D + \sum_{k=1}^{\infty} C(A)^{k-1} B z^{-k} = C(z I - A)^{-1} B + D.$$  

(4.11)

The transfer function $\hat{H}(z) = C(z I - A)^{-1} B + D$ can be directly computed from the state-space matrices $(A, B, C, D)$. Moreover, $\hat{H}(z)$ is a matrix whose entries are rational functions of $z$. Hence the transfer function provides a computationally efficient way to uniquely characterize the input-output map of a system. We will use the block notation with solid lines to indicate transfer function as in (4.11).

**Linear transformations of state-space realizations.** Consider a linear transformation of the states $x^k$ in (4.6). Specifically, suppose $Q \in \mathbb{R}^{n \times n}$ is invertible, and define $\tilde{x}^k = Q x^k$ for each $k$. The new state-space realization in terms of the new variables $\tilde{x}^k$ is

$$\begin{align*}
\tilde{x}^{k+1} &= QAQ^{-1} \tilde{x}^k + QBu^k \\
y^k &= CQ^{-1} \tilde{x}^k + Du^k,
\end{align*}$$

(4.12)

It is straightforward to check that $H$ and $\tilde{H}$ have the same transfer function. Therefore, whether we apply the linear system $H$ or $\tilde{H}$, the same input sequence $u$ will produce the same output sequence $y$, although the respective states $x^k$ and $\tilde{x}^k$ will generally be different. So although the state-space realization $(A, B, C, D)$
depend on the coordinates used to represent states $x^k$, the transfer function is invariant under linear transformations.

This invariance is the key to understanding when two optimization algorithms are the same, even if they look different as written. For example, this idea alone suffices to show that algorithms 3.1 and 3.2 are equivalent.

**Minimal realizations.** Every set of appropriately-sized state-space parameters $(A, B, C, D)$ produces a transfer matrix whose entries are rational functions of $z$. Closer inspection of the formula $\hat{H}(z) = C(zI - A)^{-1}B + D$ reveals that $\hat{H}(z) \to D$ as $z \to \infty$. Therefore, the rational entries of $\hat{H}(z)$ must be proper: the degree of the numerator cannot exceed the degree of the denominator. Moreover, the degree of the common denominator of all entries of $\hat{H}(z)$ cannot exceed $n$ (the size of the matrix $A$). Further, given any transfer matrix $\hat{H}(z)$ whose entries are proper, there exists at least one realization $(A, B, C, D)$ whose transfer function is $\hat{H}(z)$. Any realization of $\hat{H}(z)$ for which the size of $A$ is as small as possible is called minimal. All minimal realizations of $\hat{H}(z)$ are related by an invertible state transformation via a suitably chosen invertible matrix $Q$, as in (4.12).

Realizations can be non-minimal when the transfer function has factors that cancel from both the numerator and denominator. For example, the following pair of state-space equations both have the same transfer function:

\[
\hat{H}(z) = \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix} = 1 \cdot (z-1)^{-1} \cdot 1 = \frac{1}{z-1},
\]

\[
\hat{H}(z) = \begin{bmatrix} 1 & 2 \\ 0 & 3 \\ 1 & 6 \\ 0 & 0 \end{bmatrix} = [1 \ 6] \begin{bmatrix} z-1 & -2 \\ 0 & z-3 \end{bmatrix}^{-1} \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \frac{z-3}{z^2-4z+3} = \frac{1}{z-1}.
\]

We can detect when two optimization algorithms are equivalent, even when one has additional (redundant) state variables, by computing their minimal realizations. This strategy shows that algorithms 3.3 and 3.4 are equivalent.

**Inverse of state-space realization.** Consider a state-space system $H$ with realization (4.6) and for which $m = p$ (input and output dimension are the same). Is it possible to find a state-space system $H^{-1}$ that maps $y$ back to $u$? It turns out this is possible if and only if $D$ is invertible. In this case, the transfer function of $H^{-1}$ is $\hat{H}^{-1}(z)$, a matrix whose entries are rational functions of $z$. One possible state-space realization of the inverse system $H^{-1}$ is

\[
\hat{H}^{-1}(z) = \begin{bmatrix} A & B \\ C & D \end{bmatrix}^{-1} = \begin{bmatrix} A - BD^{-1}C & BD^{-1} \\ -D^{-1}C & D^{-1} \end{bmatrix}.
\]

This explicit realization can be obtained by applying the matrix inversion lemma to (4.11). We can extend this idea to partial inverses of linear systems. Suppose the input sequence $u$ is partitioned as

\[u := (u^0, u^1, \ldots) = \begin{bmatrix} u^0_0 \\ u^0_2 \\ u^1_1 \\ u^1_2 \end{bmatrix}, \quad \text{where } u^k_i \in \mathbb{R}^{m_1}, u^k_2 \in \mathbb{R}^{m_2} \text{ for all } k \geq 0\]

and similarly for $y$. The matrix $D$ and transfer matrix $\hat{H}(z)$ can also be partitioned conformally as

(4.13)

\[D = \begin{bmatrix} D_{11} & D_{12} \\ D_{21} & D_{22} \end{bmatrix} \quad \text{and} \quad \hat{H}(z) = \begin{bmatrix} \hat{H}_{11}(z) & \hat{H}_{12}(z) \\ \hat{H}_{21}(z) & \hat{H}_{22}(z) \end{bmatrix}, \quad \text{where } D_{ij} \in \mathbb{R}^{p_i \times m_j} \text{ and similarly for } \hat{H}(z).
\]

If $D_{11}$ is invertible, we can partially invert $H$ with respect to $u_1$ and $y_1$ to form a new system $H'$ that maps $(y_1, u_2) \mapsto (u_1, y_2)$. The transfer function $\hat{H}'(z)$ of the new system $H'$ satisfies

(4.14)

\[
\hat{H}'(z) = \begin{bmatrix} \hat{H}^{-1}_{11}(z) & -\hat{H}^{-1}_{11}(z)\hat{H}_{12}(z) \\ \hat{H}_{21}(z)\hat{H}^{-1}_{11}(z) & \hat{H}_{22}(z) - \hat{H}_{21}(z)\hat{H}^{-1}_{11}(z)\hat{H}_{12}(z) \end{bmatrix}.
\]

A detailed proof of (4.14) is presented in Appendix B. Note that if $D_{22}$ is invertible, we can perform a similar partial inverse with respect to the second component. When an optimization algorithm is related to another by conjugation of one of the function oracles, their transfer functions are related by (possibly partial) inversion.
5. Algorithm equivalence. We are now ready to revisit the motivating examples and formally define algorithm equivalence.

5.1. Assumptions.
We now formally state the assumptions that we have discussed informally in section 4. We assume all algorithms throughout the paper satisfy these assumptions unless specifically noted.

**Assumption 5.1.** The algorithm is causal, time-invariant, and linear.
Any algorithm satisfying assumption 5.1 can be implemented as a sequence of update equations (because it is causal) and can be written in form (4.4) (because it is linear and time-invariant).

**Assumption 5.2.** Given an oracle $\phi$, the oracle sequence produced by the algorithm is unique.
Assumption 5.2 follows if the output of $\phi$ is deterministic. It also follows if $\phi$ has internal state but is deterministic given the sequence of inputs to $\phi$ so far.

Two algorithms can only produce the same sequences if called on the same set of oracles (or on compatible oracles, for example, related by convex conjugacy). We say that two algorithms are *comparable* if they use the same or compatible oracles.

**Assumption 5.3.** When we compare two algorithms to detect equivalence or other relations, we assume that they are comparable.
We will discuss several kinds of compatible oracles in the sequel.

5.2. Oracle equivalence.
In the first motivating example, the algorithms have the same number of states, and the state sequences are equivalent up to an invertible linear transformation. We call these algorithms *state-equivalent*.

In the second motivating example, the state sequence of algorithm 3.3 can be transformed into the state sequence of algorithm 3.4 with a linear transformation. However, unlike the first motivating example, the linear transformation is not invertible; indeed, algorithm 3.4 uses fewer state variables than algorithm 3.3. Instead, recall that the sequence of calls to the gradient oracle are identical for algorithms 3.3 and 3.4. Hence these algorithms are *oracle-equivalent*.

**Definition 5.4.** Two algorithms are oracle-equivalent on a set of optimization problems if, for any problem in the set and for all possible oracles, there exist initializations for both algorithms such that the two algorithms generate the same oracle sequence.
Oracle-equivalent algorithms generate identical sequence regardless of oracles. For example, if two oracle-equivalent algorithms both call oracle $\nabla f$ and generate identical oracle sequence, they will still produce identical oracle sequence if we replace oracle $\nabla f$ to $\nabla g$ or every other possible oracle. Further, oracle equivalence is a symmetric relation. Notice that if the oracle sequences (that is, the oracles and their arguments $y^k$) are the same, then the oracles produce the same inputs $u^k$ for the linear systems of each algorithm. Hence, as shown in figure 3, oracle-equivalent algorithms have matching input $u$ and output $y$ sequences. The solid double-sided arrow indicates the sequences $y^k$ and $\tilde{y}^k$ are identical, and the sequences $u^k$ and $\tilde{u}^k$ are identical.

**Fig. 3.** Unrolled block-diagram representation of oracle equivalence.

Further, since oracle-equivalent algorithms have identical input and output sequences, many analytical properties of interest, particularly those pertaining to algorithm convergence or robustness, are preserved. For
example, suppose the target problem is to minimize $f(x)$ with $x \in \mathbb{R}^n$, with solution $x^*$ and corresponding objective value $f(x^*)$. Further suppose $f$ is convex and differentiable with oracle $\nabla f$. If two algorithms are oracle-equivalent, the sequence of gradients $\{\nabla f(x)\}$, distance to the solution $\|x - x^*\|$, and objective function values $\|f(x) - f(x^*)\|$ evolve identically, so they have the same worst-case convergence, etc: the gradient sequence and objective value are controlled by the oracle sequence. Moreover, even if the oracle is noisy (e.g., suffers from additive or multiplicative noise, or even adversarial noise), from the point of view of the oracle, the algorithms are indistinguishable and any analytical property that involves only the oracle sequence will be the same.

5.3. Shift equivalence.

 FIG. 4. Unrolled block-diagram representation of shift equivalence.

Now consider algorithms 3.5 and 3.6 from the third motivating example. They are not oracle-equivalent. However, their input and output sequences become identical after shifting algorithm 3.5 one step backward: these algorithms are shift-equivalent.

**Definition 5.5.** Two algorithms are shift-equivalent on a set of problems if, for any problem in the set and for all possible oracles, there exist initializations for both algorithms such that the oracle sequences match up to a prefix.

Shift equivalence can also be interpreted as oracle equivalence up to a shift. We depict shift equivalence graphically in figure 4. Conversely, oracle equivalence can be regarded as a special case of shift equivalence, where the oracle sequences match without any shift. Besides, similar as oracle equivalence, shift equivalence is also symmetric.

5.4. Discussion.

*One algorithm, many interpretations.* Is it useful to have many different forms of an algorithm, if all the forms are (oracle- or shift-)equivalent? Yes: different rewritings of one algorithm often yield different (“physical”) intuition. For example, algorithm 1.1 uses the current loss function for extrapolation [46]: while algorithm 1.2 seems to extrapolate from the previous loss function [10]. Equivalent algorithms can differ in memory usage, computational efficiency, or numerical stability. For example, implementations of algorithms 1.3 and 1.4 lead to different memory usage [13, 29]. In each time step $k$, algorithm 1.3 needs to store $x_k^k, x_{k+1}^k$ and $F^k()$, but algorithm 1.4 only needs to store $x_k^k$ and $x_{k+1}^k$ in memory. These different rewritings also naturally yield different generalizations, for example, by projecting different state variables.

*Limitations.* Do these formal notions of equivalence capture everything an optimization expert might mean by “equivalent algorithms”? No: an example is shown in algorithm 5.1. Algorithms 3.4 and 5.1 are related by a nonlinear state transformation, $x^k = \exp(\xi^k)$. However, none of the equivalences we have discussed capture this example. The difficulty is that algorithm 5.1 is a nonlinear algorithm, while all of our machinery for detecting algorithm equivalence requires linearity. While notions of nonlinear equivalence are certainly interesting, in this paper we will define only those types of equivalence that our framework can detect.

---

**Algorithm 5.1**

```plaintext
for $k = 1, 2, \ldots$ do
    $x^{k+1} = x^k \exp(-\frac{1}{2} \nabla f(\log x^k))$
end for
```

---
6. A characterization of oracle equivalence. In this section, we will discuss how to characterize oracle equivalence via transfer functions. Recall that oracle equivalence, introduced in section 5, characterizes an algorithm by its oracle sequence. This sequence is uniquely determined by the initialization of the algorithm (which we ignore) and the input-output map of the linear system representing the algorithm. While the state-space realization of two equivalent algorithms may differ, from subsection 4.3, recall that the transfer function of a linear system uniquely characterizes the system as an input-output map. Fortunately, using (4.11), we can directly calculate the transfer function from the state-space realization of an algorithm, and we can use equality of transfer functions to check if two algorithms are equivalent. This machinery allows us to avoid the issue of initialization (or of the optimization problem!) entirely, as we can check algorithm equivalence without ever producing a sequence of iterates.

More formally, consider two oracle-equivalent algorithms with the same number of oracle calls in each iteration. From subsection 5.2, we know that for every optimization problem, and for all possible oracles, there exist initializations for both algorithms so that the oracle sequence of the two algorithms is the same. Concretely, by picking the initializations of both algorithms appropriately, we can ensure that the first output of the linear systems match. Hence (since the oracles are the same), the first input of the linear systems match, and so the second output of the linear systems match, etc. By induction, for each possible sequence of input \( u \), they produce identical sequences of output \( y \). Then from subsection 4.3, the algorithms must have identical impulse responses and consequently identical transfer functions. In light of the previous discussion, we have proved the following proposition, since each step in the reasoning above is necessary and sufficient. We defer a detailed mathematical proof to appendix C.

**Proposition 6.1.** Algorithms with the same oracle calls in each iteration are oracle-equivalent if and only if they have identical transfer functions.

Importantly, oracle-equivalent algorithms have the same transfer function, even if they have a different number of state variables. But any realization of the algorithm must have at least as many state variables as the minimal realization of the linear system.

**Remark.** It is meaningless to compare algorithms with different oracle calls, as two algorithms are oracle equivalent if there exist initializations for both algorithms such that they generate the same oracle sequence. Hence throughout this section, we make assumption 5.3: when we compare two algorithms, we assume both algorithms use the same set of oracles. In this case, by subsection 4.3, we can always initialize both algorithms at zero to satisfy the requirement of oracle equivalence. For any algorithm that involves constant terms in its state-space realization, we can affinely transform it into an equivalent state-space realization without constant terms. Under this affine transformation, zero still satisfies the requirements of initialization for oracle-equivalence. This justifies our approach to characterize oracle equivalence with transfer functions and ignore the initializations. Further, from (4.7), the effect of initialization diminishes as time step goes to infinity, thus, asymptotically initialization does not affect the behavior of an algorithm such as convergence properties.

Oracle-equivalent algorithms have identical oracle sequences and hence converge to the same fixed point (if they converge). Suppose algorithm \( \mathcal{A}_1 : \mathcal{X} \to \mathcal{X} \) with (nonlinear) oracle \( \phi : \mathcal{X} \to \mathcal{X} \) and state-space realization \( (A_1, B_1, C_1, D_1) \), converges to a fixed point \( (y^*, u^*, x^*) \) that satisfies

\[
\begin{align*}
x^* &= A_1 x^* + B_1 u^* \\
y^* &= C_1 x^* + D_1 u^* \\
u^* &= \phi(y^*).
\end{align*}
\]  

(6.1)

If algorithm \( \mathcal{A}_2 \) is oracle-equivalent to \( \mathcal{A}_1 \), \( \mathcal{A}_2 \) converges to a fixed point \( (y^*, u^*, \hat{x}^*) \) that has the same output and input as the fixed point of \( \mathcal{A}_1 \); however, the state \( \hat{x}^* \) may not be the same, or even have the same dimension.

Further, if there is an invertible linear map \( Q \) between the states of \( \mathcal{A}_1 \) and \( \mathcal{A}_2 \) and \( (y^*, u^*, x^*) \) is a fixed point of \( \mathcal{A}_1 \), then \( (y^*, u^*, Qx^*) \) is a fixed point of \( \mathcal{A}_2 \). We can use this fact to derive a relation between the state-space realizations of the two algorithms: the fixed point equation for \( \mathcal{A}_2 \) can be written as

\[
\begin{align*}
Q x^* &= QA_1 Q^{-1} Q x^* + QB_1 u^* \\
y^* &= C_1 Q^{-1} Q x^* + D_1 u^* \\
u^* &= \phi(y^*),
\end{align*}
\]  

(6.2)
which shows that the state-space realization of $A_2$ is
\begin{equation}
(6.3) \quad \begin{bmatrix} QA_1Q^{-1} \\ C_1Q^{-1} \end{bmatrix} \begin{bmatrix} QB_1 \\ D_1 \end{bmatrix},
\end{equation}
which can be obtained by (4.12).

**6.1. Motivating examples: proof of equivalence.** Now, we will revisit the first and second motivating examples and apply proposition 6.1 to show equivalence. We perform the computation using the gradient oracle ($\nabla f$) as the oracle to compute the state-space realizations and transfer functions.

*Algorithms 3.1 and 3.2.* The state-space realization and transfer function of algorithm 3.1 are shown as
\begin{equation}
\hat{H}_1(z) = \begin{bmatrix} 2 & -1 \\ 1 & 0 \\ 2 & -1 \end{bmatrix} \begin{bmatrix} -\frac{1}{10} \\ 0 \end{bmatrix} = [2 -1] \left( z - \begin{bmatrix} 2 & -1 \\ 1 & 0 \end{bmatrix} \right)^{-1} \begin{bmatrix} -\frac{1}{10} \\ 0 \end{bmatrix} = \frac{-2z + 1}{10(z - 1)^2}.
\end{equation}

The state-space realization and the transfer function of algorithm 3.2 are
\begin{equation}
\hat{H}_2(z) = \begin{bmatrix} 1 & -1 \\ 0 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} -\frac{1}{10} \\ 0 \end{bmatrix} = [1 0] \left( z - \begin{bmatrix} 1 & -1 \\ 0 & 1 \end{bmatrix} \right)^{-1} \begin{bmatrix} -\frac{1}{10} \\ 0 \end{bmatrix} = \frac{-2z + 1}{10(z - 1)^2}.
\end{equation}

Hence we see algorithms 3.1 and 3.2 have the same transfer function, so by proposition 6.1 they are oracle-equivalent. In fact, since the algorithms have the same number of state variables, there exists an invertible linear transformation $Q = \begin{bmatrix} 2 & -1 \\ -1 & 1 \end{bmatrix}$ to convert the state-space realization of algorithm 3.1 to the state-space realization of algorithm 3.2 following (4.12).

*Algorithms 3.3 and 3.4.* The state-space realization and transfer function of algorithm 3.3 are
\begin{equation}
\hat{H}_3(z) = \begin{bmatrix} 3 & -2 \\ 1 & 0 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} \frac{1}{5} \\ 0 \end{bmatrix} = [-1 2] \left( z - \begin{bmatrix} 3 & -2 \\ 1 & 0 \end{bmatrix} \right)^{-1} \begin{bmatrix} \frac{1}{5} \\ 0 \end{bmatrix} = -\frac{1}{5(z - 1)}.
\end{equation}

The state-space realization and transfer function of algorithm 3.4 are
\begin{equation}
\hat{H}_4(z) = \begin{bmatrix} 1 & -\frac{1}{5} \\ 1 & 0 \end{bmatrix} = [1] (z - [1])^{-1} \begin{bmatrix} -\frac{1}{5} \\ 0 \end{bmatrix} = -\frac{1}{5(z - 1)}.
\end{equation}

Algorithms 3.3 and 3.4 have the same transfer function, so by proposition 6.1 they are oracle-equivalent. On the other hand, they have different numbers of states. Consider the invertible linear transformation $Q = \begin{bmatrix} -1 & 2 \\ 0 & 1 \end{bmatrix}$.

Applying $Q$ to the state-space realization of algorithm 3.3 leads to
\begin{equation}
\begin{bmatrix} 1 & 0 & -\frac{1}{5} \\ -1 & 2 & 0 \\ 1 & 0 & 0 \end{bmatrix},
\end{equation}
where we have used dashed lines to demarcate the blocks in the state-space realization. This has the same minimal realization as algorithm 3.4 by subsection 4.3.

\[ \begin{bmatrix} 1 & -\frac{1}{5} \\ 1 & 0 \end{bmatrix}. \]

Note that the state-space realization of algorithm 3.4 is a minimal realization. This shows the reason why algorithms 3.3 and 3.4 are equivalent even if they have different numbers of states.
Now we show how the sausage was made. Algorithm 3.3 was designed by starting with the more complex Triple momentum algorithm 6.1 [27, 45] and choosing parameters of the algorithm so its transfer function matched algorithm 3.4.

Algorithm 6.1 Triple momentum algorithm

\[
\begin{aligned}
&\text{for } k = 0, 1, 2, \ldots \text{ do} \\
&x_{k+1} = (1 + \beta)x_k^1 - \beta x_k^2 - \alpha \nabla f((1 + \eta)x_k^1 - \eta x_k^2) \\
x_{k+1}^2 = x_k^1 \\
\end{aligned}
\]

end for

The state-space realization and transfer function of algorithm 6.1 are

\[
H_\tau(z) = \begin{bmatrix}
1 + \beta & -\beta & -\alpha \\
1 & 0 & 0 \\
1 + \eta & -\eta & 0 \\
\end{bmatrix} = -\frac{\alpha((\eta + 1)z - \eta)}{(z - 1)(z - \beta)}.
\]

We now demand that (6.4)(right) must equal the transfer function of algorithm 3.4 for all values of \(z\), resulting in the equations

\[
\begin{aligned}
5\alpha(\eta + 1) &= 1 \\
5\alpha\eta &= \beta.
\end{aligned}
\]

We solve for the parameters \(\alpha, \eta\) and \(\beta\) to find a solution \(\alpha = -\frac{1}{5}, \beta = 2\) and \(\eta = -2\) to (6.5) that corresponds to algorithm 3.3. Other solutions exist: for example, \(\alpha = 1, \beta = -4\) and \(\eta = -\frac{4}{5}\) solves (6.5) and yields another (different!) algorithm equivalent to algorithm 3.4.

7. A characterization of shift equivalence. We can also characterize shift equivalence using transfer functions. Suppose an algorithm uses more than one oracle, and the call to the second oracle depends on the value of the first. Take algorithm 3.5 as example: at iteration \(k\), the first update equation calls the oracle \(\text{prox}_f\) to compute \(x_{k+1}^1 = \text{prox}_f(x_k^1)\), and the second update equation calls the oracle \(\text{prox}_g\) to compute \(x_{k+1}^2 = \text{prox}_g(2x_{k+1}^3 - x_k^3)\). This second update relies on the value of \(x_{k+1}^1\). Imagine now that we reorder the update equations by some permutation. Generally this change produces an entirely different algorithm. But if the permutation is a cyclic permutation, the order of the oracle calls is preserved. In the example of algorithm 3.5, we could start with the update equation \(x_{k+1}^2 = \text{prox}_g(2x_{k+1}^3 - x_k^3)\) and produce exactly the same sequence of oracle calls (after the first) by initializing \(x_{k+1}^1\) and \(x_{k+1}^2\) appropriately. This new algorithm is shift-equivalent to algorithm 3.5 by definition 5.5.

Algorithm 3.5 has three update equations, and so there are two other algorithms that may be produced by cyclic permutations of algorithm 3.5, shown below as algorithms 7.1 and 7.2.

Algorithm 7.1

\[
\begin{aligned}
&\text{for } k = 0, 1, 2, \ldots \text{ do} \\
&x_{k+1}^1 = \text{prox}_f(2x_k^1 - x_k^3) \\
x_{k+1}^3 = x_k^3 + x_{k+1}^1 - x_k^1 \\
x_{k+1}^1 = \text{prox}_f(x_{k+1}^3) \\
\end{aligned}
\]

end for

Both are shift-equivalent to algorithm 3.5, but algorithm 7.2 is also oracle-equivalent to algorithm 3.5. (We will revisit and formally prove this result later.) It is easy to see why: the oracles \(\text{prox}_f\) and \(\text{prox}_g\) are called in the same order in algorithms 3.5 and 7.2, but in the opposite order in algorithm 7.1.

We introduce notation to generalize this idea to more complex algorithms. Consider an algorithm \(\mathcal{A}\) that consists of \(m\) update equations and makes \(n\) sequential oracle calls in each iteration. We insist that no update equation may contain more than one oracle call, so \(m \geq n\). At iteration \(k\), the algorithm generates states \(x_1^k, \ldots, x_m^k\), outputs \(y_1^k, \ldots, y_n^k\), and inputs \(u_1^k, \ldots, u_n^k\), respectively. Consider any permutation \(\tilde{\pi}\) of the sequence \((m) = (1, \ldots, m)\). We call algorithm \(\mathcal{B} = P_{\tilde{\pi}}\mathcal{A}\) a permutation of algorithm \(\mathcal{A}\) if \(\mathcal{B}\) performs the
update equations of $A$ in the order $\tilde{\pi}$ at each iteration. The algorithms $A$ and $B$ are shift-equivalent if and only if $\tilde{\pi}$ is a cyclic permutation of $(m)$.

**Proposition 7.1.** An algorithm and any of its cyclic permutations are shift-equivalent. Any two shift-equivalent algorithms are equivalent to cyclic permutations of each other.

**Proof.** We provide a proof sketch here, and defer a detailed proof to appendix D. Let us name the oracle calls of the original algorithm $A$ so that the oracles are called in order $(n)$.

Cyclic permutation implies shift equivalence. Suppose $B = P_\pi A$ where $\tilde{\pi}$ is a cyclic permutation of $(m)$. The permutation of update equations may reorder the oracle calls within one iteration, so that the oracle calls in algorithm $B$ follow a cyclic permutation $\pi$ of $(n)$ (possibly, the identity). Hence $A$ and $B$ are shift-equivalent. (If the permutation is the identity, then the algorithms are also oracle-equivalent.)

Shift equivalence implies cyclic permutation. Suppose algorithms $A$ and $B$ are shift-equivalent. If they are also oracle-equivalent, then they can be written using the same set of update equations. If they are not oracle-equivalent, we can always find a cyclic permutation of the update equations of $A$ that produces the same oracle sequence as $B$. Therefore $A$ and $B$ are equivalent to cyclic permutations of each other. (In the first case, the permutation is the identity.)

### 7.1. Reordering oracle calls

Most optimization algorithms proceed by sequential updates, each of which depends on the previous update. However, for completeness, we consider a more general class of equivalences that arises for algorithms whose oracle updates have a more complex dependency structure. We may express the order of the oracle calls at each iteration using a directed graph, where the graph has edge from oracle $i$ to oracle $j$ if oracle call $j$ depends on the result of oracle call $i$ (within the same iteration). In other words, within the iteration we must call oracle $i$ before oracle $j$. We call this directed graph the oracle dependence graph (ODG) of the algorithm.

An example is provided below as algorithm 7.3. Note that we are not aware of any practical algorithm for optimization with this ODG. It is constructed only for illustration.

#### Algorithm 7.3

```plaintext
for $k = 0, 1, 2, \ldots$ do
    $x_1^{k+1} = x_2^k - t \nabla f(x_2^k)$
    $x_2^{k+1} = x_1^{k+1} - t \nabla g(x_1^{k+1})$
    $x_3^{k+1} = x_1^{k+1} - t \nabla h(x_1^{k+1})$
    $x_4^{k+1} = \text{prox}_{t f}((7/2)x_2^k + 1/2 x_3^{k+1})$
end for
```

#### Algorithm 7.4

```plaintext
for $k = 0, 1, 2, \ldots$ do
    $x_1^{k+1} = x_2^k - t \nabla f(x_2^k)$
    $x_2^{k+1} = x_1^{k+1} - t \nabla h(x_1^{k+1})$
    $x_3^{k+1} = x_1^{k+1} - t \nabla g(x_1^{k+1})$
    $x_4^{k+1} = \text{prox}_{t f}((7/2)x_2^k + 1/2 x_3^{k+1})$
end for
```

Figure 5 expresses the dependency of oracle calls within each iteration of algorithm 7.3. At each iteration, oracle calls 2 ($\nabla g$) and 3 ($\nabla h$) depends on the result of oracle call 1 ($\nabla f$); oracle call 4 ($\text{prox}_{t f}$) depends on the results of oracle calls 1, 2, and 3.

![Directed graph representing dependency of oracle calls in algorithm 7.3.](image_url)

An algorithm is always written as a sequence of update equations. But some algorithms might have a directed graph that may be written as a sequence (with all edges pointing forward) in more than one way, and so can be implemented as a sequence of oracle calls in more than one way. For illustration, consider algorithms 7.3 and 7.4. At each iteration, the oracle calls of algorithms 7.3 and 7.4 are identical: that is, calls to oracles $\nabla f$, $\nabla g$, $\nabla h$, and $\text{prox}_{t f}$ are identical. The only difference is that the oracle calls $\nabla g$ and $\nabla h$ are swapped in the oracle sequence at each iteration. Notice that the state-space realizations of these
algorithms still have the same transfer function (after swapping the second and third columns and rows), consistent with the fact that algorithms 7.3 and 7.4 share the same directed graph of oracle calls (figure 5).

We know of no practical optimization algorithm like this. However, were one to be discovered, we would suggest an expanded definition of oracle equivalence: two algorithms are oracle-equivalent if there exists a way of writing each algorithm as a sequence of updates so that both algorithms have the same sequence of oracle calls. The transfer function still identifies algorithms that are oracle-equivalent in this expanded sense.

The oracle calls in an algorithm at each iteration are always written in sequential form. This sequential form is lost in the state-space realization of the algorithm. However, the order (dependency) of oracle calls is encoded in the $D$ matrix of the state-space realization. In this sense, the $D$ matrix encodes the adjacency matrix of the directed graph. We have $D_{ij} \neq 0$ if and only if oracle call $i$ depends on the results of oracle call $j$ at each iteration. For example, in the state-space realization of algorithm 7.3, the $D$ matrix is

$$
\begin{bmatrix}
0 & 0 & 0 & 0 \\
-t & 0 & 0 & 0 \\
-t & 0 & 0 & 0 \\
-t & -\frac{1}{2}t & -\frac{1}{2}t & 0
\end{bmatrix}.
$$

In light of this discussion, we can strengthen proposition 7.1 to proposition 7.2.

**Proposition 7.2.** An algorithm and any of its cyclic permutations are shift-equivalent; further, if they share the same $D$ matrix in their state-space realizations, they are also oracle-equivalent. Any two shift-equivalent algorithms are equivalent to cyclic permutations of each other.

If an algorithm contains $m$ update equations and $n$ oracle calls at each iteration ($m \geq n$), there are $m$ possible cyclic permutations on the update equations. According to the $D$ matrix in the state-space realization, we can group the $m$ cyclic permutations into $n$ distinct equivalent classes. Algorithms within each equivalence class are oracle-equivalent and shift-equivalent, while algorithms in different equivalent classes are only shift-equivalent. The $n$ distinct equivalence classes correspond to the $n$ cyclic permutations of the original order of oracle calls ($n$).

**7.2. Characterization of cyclic permutation.**

In the remainder of this paper, let us restrict our attention to algorithms for which a (cyclic) permutation of the algorithm changes the update order of oracle calls within one iteration, or in other words, changes the $D$ matrix in the state-space realization. In this way, we call algorithm $\mathcal{B} = P_\pi \mathcal{A}$ a permutation of algorithm $\mathcal{A}$ if $\mathcal{B}$ performs the update equations of $\mathcal{A}$ in a different order such that the update order of oracle calls of $\mathcal{B}$ is $\pi$ at each iteration.

Suppose $\mathcal{A}$ has state-space realization $(A, B, C, D)$, and $\mathcal{B} = P_\pi \mathcal{A}$ where $\pi = (j + 1, \ldots, n, 1, \ldots, j)$ for $1 < j < n$ is a cyclic permutation of $(n)$. We will show how to recognize this relationship between the algorithms using their transfer functions. Partition the oracle calls into two parts, $(1, \ldots, j)$ and $(j+1, \ldots, n)$, and partition the input and output sequences in the same way: $\bar{u}_1, \bar{u}_2$ for inputs and $\bar{y}_1, \bar{y}_2$ for outputs. The state-space realization $L_{\mathcal{A}}$ and transfer function $\hat{H}_{\mathcal{A}}(z)$ can also be partitioned accordingly as

(7.1) 
$$
L_{\mathcal{A}} = \begin{bmatrix}
A & B_1 & B_2 \\
C_1 & D_{11} & D_{12} \\
C_2 & D_{21} & D_{22}
\end{bmatrix},
$$

$$
\hat{H}_{\mathcal{A}}(z) = \begin{bmatrix}
C_1(zI - A)^{-1}B_1 + D_{11} & C_1(zI - A)^{-1}B_2 + D_{12} \\
C_2(zI - A)^{-1}B_1 + D_{21} & C_2(zI - A)^{-1}B_2 + D_{22}
\end{bmatrix} = \begin{bmatrix}
\hat{H}_{11}(z) & \hat{H}_{12}(z) \\
\hat{H}_{21}(z) & \hat{H}_{22}(z)
\end{bmatrix}.
$$

Now we can say how the transfer function of an algorithm is related to that of its cyclic permutation. Recall that by assumption 5.3, when we compare transfer functions to detect shift equivalence (or cyclic permutations), both algorithms call the same set of oracles in each iteration.

**Proposition 7.3.** In state notation as in (7.1) and assume $D_{12} = 0$. Then $\mathcal{B}$ is equivalent to $P_\pi \mathcal{A}$ if and only if the transfer function of $\mathcal{B}$ satisfies

(7.2) 
$$
\hat{H}_{\mathcal{B}}(z) = \begin{bmatrix}
\hat{H}_{11}(z) & z\hat{H}_{12}(z) \\
\hat{H}_{21}(z)/z & \hat{H}_{22}(z)
\end{bmatrix}.
$$
Proof. We provide a proof sketch here and defer a detailed proof to appendix E. The state-space realization of $P_A$ is

$$
\begin{bmatrix}
A & B_1 & 0 & B_2 \\
0 & 0 & I & 0 \\
C_1A & C_1B_1 & D_{11} & C_1B_2 \\
C_2 & D_{21} & 0 & D_{22}
\end{bmatrix}.
$$

From the state-space realization, we may compute the transfer function as

$$
\hat{H}_S(z) = \begin{bmatrix} C_1(zI - A)^{-1}B_1 + D_{11} & zC_1(zI - A)^{-1}B_2 \\
C_2(zI - A)^{-1}B_1/z + D_{21}/z & C_2(zI - A)^{-1}B_2 + D_{22} \end{bmatrix} = \begin{bmatrix} \hat{H}_{11}(z) & z\hat{H}_{12}(z) \\
\hat{H}_{21}(z)/z & \hat{H}_{22}(z) \end{bmatrix}.
$$

Finally, note two algorithms are equivalent if and only if they have identical transfer functions by proposition 6.1.

We have assumed that $D_{12} = 0$ for algorithm $A$. This assumption is quite weak. In fact, $D_{12}$ must be 0 for any algorithm $A$ that can be represented as a causal linear time-invariant system. Here, causal means that we can implement the algorithm by calling state update equations sequentially. To see this, suppose the state update equations have been arranged in this order, and use (4.5) to write down the matrix representation of the infinite dimensional map $H$ that maps input $u$ to output $y$ corresponding to $A$ as (7.4):

$$
H = \begin{bmatrix}
D_{11} & D_{12} & 0 & 0 & 0 & \cdots \\
D_{21} & D_{22} & 0 & 0 & 0 & \cdots \\
C_1B_1 & C_1B_2 & D_{11} & D_{12} & 0 & \cdots \\
C_2B_1 & C_2B_2 & D_{21} & D_{22} & 0 & \cdots \\
C_1AB_1 & C_1AB_2 & C_1B_1 & C_1B_2 & D_{11} & D_{12} & \cdots \\
C_2AB_1 & C_2AB_2 & C_2B_1 & C_2B_2 & D_{21} & D_{22} & \cdots \\
& \cdots & \cdots & \cdots & \cdots & \cdots & \cdots
\end{bmatrix}
$$

We can see that map $H$ is (block) Toeplitz. Further, if algorithm $A$ is causal, map $H$ must be lower-triangular, and so $D_{12}$ must be 0.

By causality, at each iteration the former oracle calls must be independent with the latter oracle calls while the latter calls can depend on the former calls. This indicates that there are no directed cycles in the directed graph representing oracle calls at each iteration for any causal algorithm. In other words, the graph is a directed acyclic graph (DAG). This is consistent with the fact that any causal algorithm has a lower-triangular $D$ matrix (lower-triangular adjacency matrix of the directed graph).

Note that algorithms are not always written with state update equations ordered causally: for example, the state-space realization (7.3) has a non-zero $D_{12}$ block. However, we may reorder these equations so that each equation depends only on previously-computed quantities to reveal that the iteration is causal; after this rearrangement, the new $D_{12}$ block is 0. We discuss permutations further in appendix F.

The fixed points of an algorithm and its cyclic permutations are the same up to a permutation, as stated by proposition 7.4.

**Proposition 7.4.** If algorithm $A$ converges to a fixed point $(\bar{y}_1', \bar{y}_2', \bar{u}_1', \bar{u}_2', x^*)$, then its cyclic permutation $P_A$ converges to fixed point $(\bar{y}_2', \bar{y}_1', \bar{u}_2', \bar{u}_1', x^*)$.

A detailed proof is provided in appendix G.

**7.3. Applications: proof of shift equivalence.**

**Algorithms 3.5 and 3.6.** Now, we can revisit algorithms 3.5 and 3.6 in the third motivating example and show that they are shift-equivalent. Here the oracles of algorithms 3.5 and 3.6 are $proxf$ and $proxg$. The transfer function of algorithm 3.5 is

$$
\hat{H}_S(z) = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 1 \\
0 & 0 & 1 & -1 & 1 \\
0 & 0 & 1 & 0 & 0 \\
0 & 0 & -1 & 2 & 0
\end{bmatrix} = \begin{bmatrix} -\frac{1}{2z^{-1}} & \frac{1}{z^{-2}} \\
\frac{1}{2z^{-2}} & -\frac{1}{z^{-1}} \end{bmatrix}.
$$
The transfer functions of algorithm 7.6 is

\[
\hat{H}_6(z) = \begin{bmatrix}
1 & -1 & 0 & 1 \\
0 & 0 & 1 & 0 \\
1 & -1 & 0 & 1 \\
1 & -1 & 0 & 0 \\
\end{bmatrix} = \begin{bmatrix}
\frac{-1}{2z-1} & \frac{z}{z-1} \\
\frac{z}{z-1} & \frac{-1}{z-1} \\
\end{bmatrix}.
\]

From propositions 7.1 and 7.3, we know that they are shift-equivalent and equivalent up to a cyclic permutation.

**Algorithms 7.1 and 7.2.** Here we revisit algorithms 7.1 and 7.2 at the beginning of this chapter and show their relations with algorithm 3.5. The oracles are prox_\_f and prox_\_g. The transfer function of algorithm 7.1 is

\[
\hat{H}_7(z) = \begin{bmatrix}
0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 \\
-1 & 0 & 0 & 0 \\
-1 & 0 & 0 & 1 \\
\end{bmatrix} = \begin{bmatrix}
\frac{-1}{2z-1} & \frac{z}{z-1} \\
\frac{z}{z-1} & \frac{-1}{z-1} \\
\end{bmatrix}.
\]

The transfer function of algorithm 7.2 is

\[
\hat{H}_8(z) = \begin{bmatrix}
0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 \\
-1 & 1 & 1 & 0 \\
-1 & 1 & 1 & 0 \\
\end{bmatrix} = \begin{bmatrix}
\frac{-1}{2z-1} & \frac{z}{z-1} \\
\frac{z}{z-1} & \frac{-1}{z-1} \\
\end{bmatrix}.
\]

From propositions 7.1 and 7.3, we know that algorithms 3.5 and 7.1 are shift-equivalent and equivalent up to a cyclic permutation. From proposition 6.1, we know algorithms 3.5 and 7.2 are oracle-equivalent, thus they are also shift-equivalent.

**Algorithm 7.5 Douglas-Rachford splitting**

\[
\text{for } k = 0, 1, 2, \ldots \text{ do}
\]

\[
x_1^{k+1} = \text{prox}_f(x_3^k)
\]

\[
x_2^{k+1} = \text{prox}_{\epsilon g(L)}(2x_1^{k+1} - x_3^k)
\]

\[
x_3^{k+1} = x_3^k + x_2^{k+1} - x_1^{k+1}
\]

\[
\text{end for}
\]

**Algorithm 7.6 ADMM**

\[
\text{for } k = 0, 1, 2, \ldots \text{ do}
\]

\[
\xi_1^{k+1} = \text{argmin}_\xi \{g(\xi) + \frac{\rho}{2} \| A\xi + B\xi_2^k - c + \xi_3^k \|^2 \}
\]

\[
\xi_2^{k+1} = \text{argmin}_\xi \{f(\xi) + \frac{\rho}{2} \| A\xi_1^k + B\xi - c + \xi_3^k \|^2 \}
\]

\[
\xi_3^{k+1} = \xi_3^k + A\xi_1^k + B\xi_2^k + c
\]

\[
\text{end for}
\]

**Douglas-Rachford splitting and ADMM.** Consider a last example of algorithm permutation: Douglas-Rachford splitting (DR) (algorithm 7.5 [15,17]) and the alternating direction method of multipliers (ADMM) (algorithm 7.6 [38, §8]). Suppose that linear operator L is invertible, A = L^{-1}, B = -I, and c = 0 in (4.1). Then both DR and ADMM solve problem (4.1) [6,28,47], and the update equations of ADMM can be simplified as algorithm 7.7. Further, we assume \( \rho = 1/t \) in ADMM. We will compute the transfer function of

**Algorithm 7.7 Simplified ADMM**

\[
\text{for } k = 0, 1, 2, \ldots \text{ do}
\]

\[
\xi_1^{k+1} = L\text{prox}_{\rho g(L)}(\xi_2^k - \xi_3^k)
\]

\[
\xi_2^{k+1} = \text{prox}_{\rho f}(L^{-1}\xi_1^{k+1} + \xi_3^k)
\]

\[
\xi_3^{k+1} = \xi_3^k + L^{-1}\xi_1^{k+1} - \xi_2^{k+1}
\]

\[
\text{end for}
\]

both algorithms using prox_\_f and prox_\_g_\_L as the oracles. The transfer function of DR is

\[
\hat{H}_{10}(z) = \begin{bmatrix}
0 & 0 & 0 & I & 0 \\
0 & 0 & 0 & 0 & I \\
0 & 0 & I & -I & 0 \\
0 & 0 & I & 0 & 0 \\
0 & 0 & -I & 2I & 0 \\
\end{bmatrix} = \begin{bmatrix}
\frac{-1}{2z-1} & \frac{z}{z-1} \\
\frac{z}{z-1} & \frac{-1}{z-1} \\
\end{bmatrix}.
\]
and the transfer function of ADMM is

\[
(7.6) \quad \hat{H}_{11}(z) = \begin{bmatrix}
0 & 0 & 0 & 0 & L \\
0 & 0 & 0 & I & 0 \\
0 & 0 & I & -I & I \\
0 & 0 & I & 0 & 1 \\
0 & 0 & I & 0 & 0
\end{bmatrix} = \begin{bmatrix}
-\frac{1}{z^2-1}I & \frac{-1}{z^2-1}I \\
\frac{-1}{z^2-1}I & \frac{-1}{z^2-1}I
\end{bmatrix}.
\]

From propositions 7.1 and 7.3, we know that DR and ADMM (with \( \rho = 1/t \)) are shift-equivalent and that DR is equivalent to a cyclic permutation of ADMM. In fact, it is also possible to write the state-space realization for each algorithm using the gradient (or subgradient) of \( f \) and \( g \) as the oracle. The transfer functions depend on the choice of oracle, but in either case, we obtain the same results: the algorithms are shift-equivalent. We discuss the details further in appendix H. We can write the state-space realizations of DR and ADMM using the (sub)gradients as oracles in appendix H: the corresponding \( D_{12} \) blocks are still zero and thus still satisfy causality.

8. **Algorithm repetition.** In previous sections, we have defined equivalence between algorithms with the same number of oracle calls in each iteration. This section considers how to identify relations between two algorithms when the number of oracles in each iteration differs. For example, we would like to detect the same number of oracle calls in each iteration. This section considers how to identify relations between two algorithms when the number of oracles in each iteration differs. For example, we would like to detect the same number of oracle calls in each iteration. This section considers how to identify relations between two algorithms when the number of oracles in each iteration differs. For example, we would like to detect the same number of oracle calls in each iteration.

Consider an algorithm \( A \). Given a problem and an initialization, the algorithm will generate state sequence \( (x^k_A)_{k \geq 0} \), input sequence \( (u^k_A)_{k \geq 0} \), and output sequence \( (y^k_A)_{k \geq 0} \), respectively. Specifically, the update at time step \( k \) can be written as \( x^{k+1}_A = A(x^k_A) \). Suppose we have another algorithm \( B \) such that \( B = A^2 \): repeating \( A \) twice gives the same result as \( B \). We call \( B \) a repetition of \( A \).

Just as in the previous sections, algorithm repetition can be characterized by the transfer function. Here, assumption 5.3 ensures the algorithms compared call the same set of oracles, although the number of times each oracle is called may be different.

**Proposition 8.1.** Suppose \( A \) has state-space realization \( (A, B, C, D) \). Then \( B \) is equivalent to \( A^2 \) if and only if its transfer function has the form

\[
(8.1) \quad \begin{bmatrix}
C(zI - A)^{-1}AB + D & C(zI - A^2)^{-1}B \\
CA(zI - A)^{-1}AB + CB & CA(zI - A^2)^{-1}B + D
\end{bmatrix}.
\]

Detailed proof of proposition 8.1 is provided in appendix I.

| Algorithm 8.1 Gradient method |
|-------------------------------|
| **for** \( k = 0, 1, 2, \ldots \) **do** |
| \( x^{k+1} = x^k - t\nabla f(x^k) \) |
| **end for** |

| Algorithm 8.2 Repetition of gradient method |
|-------------------------------|
| **for** \( k = 0, 1, 2, \ldots \) **do** |
| \( \xi^{k+1} = \xi^k - t\nabla f(\xi^k) \) |
| \( \xi^{k+1}_1 = \xi^{k+1}_2 - t\nabla f(\xi^{k+1}_2) \) |
| **end for** |

One example of repetition consists the gradient method algorithm 8.1 and its repetition algorithm 8.2. Both call the same set of oracles (\( \nabla f \)). The transfer functions of each algorithm are computed as \( \hat{H}_{12}(z) \) and \( \hat{H}_{13}(z) \) respectively:

\[
\hat{H}_{12}(z) = \begin{bmatrix}
1 & t \\
1 & 0
\end{bmatrix} = \frac{-t}{z-1}, \quad \hat{H}_{13}(z) = \begin{bmatrix}
1 & -t & -t \\
1 & 0 & 0 \\
1 & -t & 0
\end{bmatrix} = \begin{bmatrix}
-\frac{t}{z^2-1} & -\frac{t}{z^2-1} & -\frac{t}{z^2-1} \\
-\frac{t}{z^2} & -\frac{t}{z^2} & -\frac{t}{z^2}
\end{bmatrix}.
\]

Proposition 8.1 reveals how the transfer function changes when an algorithm is repeated twice. In fact, we can identify an algorithm that has been repeated arbitrarily many times. Suppose algorithm \( C \) is \( A \) repeated \( n \geq 1 \) times: \( C = A^n \).

**Proposition 8.2.** Suppose \( A \) has state-space realization \( (A, B, C, D) \). Then \( C \) is equivalent to \( A^n \) for \( n \geq 1 \) if and only if \( C \) has a transfer function given by (8.3).
Proof. Sufficiency. We can represent \( C \) with state-space realization

\[
\begin{bmatrix}
    A^n & A^{n-1}B & \cdots & AB & B \\
    C & D & \cdots & 0 & 0 \\
    CA & CB & D & \cdots & 0 \\
    \vdots & \vdots & \ddots & \ddots & \vdots \\
    CA^{n-1} & CA^{n-2}B & \cdots & CB & D
\end{bmatrix}.
\]

(8.2)

Note that \((zI - A^n)^{-1}A^l = A^l(zI - A^n)^{-1}\) for any \( n \) and \( l \). Let \( \tilde{C} = C(zI - A^n)^{-1} \), and compute the transfer function of \( \tilde{C} \):

\[
\begin{bmatrix}
    \tilde{C}A^{n-1}B + D & \tilde{C}A^{n-2}B & \cdots & \tilde{C}AB & \tilde{C}B \\
    \tilde{C}A^nB + CB & \tilde{C}A^{n-1}B + D & \cdots & \tilde{C}A^2B & \tilde{C}AB \\
    \vdots & \vdots & \ddots & \ddots & \vdots \\
    \tilde{C}A^{2n-2}B + CA^{n-2}B & \tilde{C}A^{2n-3}B + CA^{n-3}B & \cdots & \tilde{C}A^nB + CB & \tilde{C}A^{n-1}B + D
\end{bmatrix}.
\]

(8.3)

Necessity is provided by proposition 6.1 since the transfer function uniquely characterizes an equivalence class of algorithms.

Remark. Proposition 8.1 is a special case of proposition 8.2 when \( n = 2 \). The dimension of transfer function of \( C \) is \( n \) times the dimension of transfer function of \( A \). Similarly, the dimension of input and output of \( C \) is \( n \) times the dimension of the input and output of \( A \). At time step \( k \), we have \( y^k = (y_A^{nk}, \ldots, y_A^{(n+1)k-1}) \) and \( u^k = (u_A^{nk}, \ldots, u_A^{(n+1)k-1}) \).

Just as for oracle equivalence and cyclic permutations, the fixed points of an algorithm and its repetitions are related, as shown in proposition 8.3.

**Proposition 8.3.** If algorithm \( A \) converges to a fixed point \((y^*, u^*, x^*)\), then its repetition \( A^n \) for \( n \geq 1 \) converges to fixed point \((y', u', x')\), with \( y' = y^* \otimes 1^n \) and \( u' = u^* \otimes 1^n \). Here \( \otimes \) is the Kronecker product and \( 1^n \) is an \( n \) dimensional vector whose entries are all ones.

Detailed proof is provided in appendix J. Since \( A^n \) repeats \( A \) \( n \) times, the input and output of the fixed point of \( A^n \) are obtained by repeating the input and output on the corresponding fixed point of \( A \) \( n \) times.

Repetition gives us many more ways to combine algorithms into complex and unwieldy (but convergent) new methods. We can repeat a sequence of iterations from different algorithms and regard them together as a new algorithm. Suppose we choose \( n \) algorithms \( A_1, \ldots, A_n \) with state-space realizations \((A_1, B_1, C_1, D_1), \ldots, (A_n, B_n, C_n, D_n)\) and run one iteration of each as a single iteration of our new monster algorithm. For simplicity, suppose the state-space realization matrices \( A_i, B_i, C_i, D_i \) for each algorithm \( A_i \) have the same dimensions as all others \( i = 1, \ldots, n \). (Otherwise the result is harder to write down, but still straightforward to compute.) Then we can represent the resulting monster algorithm with transfer function

\[
\begin{bmatrix}
    \prod_{i=1}^{n} A_i & \prod_{i=n}^{2} A_i B_1 & \cdots & A_n B_{n-1} & B_n \\
    C_1 & D_1 & 0 & \cdots & 0 \\
    C_2 A_1 & C_2 B_1 & D_2 & \cdots & 0 \\
    \vdots & \vdots & \ddots & \ddots & \vdots \\
    C_n \prod_{i=n-1}^{1} A_i & C_n \prod_{i=n-1}^{2} A_i B_1 & \cdots & C_n B_{n-1} & D_n
\end{bmatrix}.
\]

(8.4)

Hence one way to develop a new optimization algorithm would be to combine existing algorithms into a new monster algorithm with similar convergence properties but (perhaps) new exciting interpretations. For example, we could combine gradient descent with the proximal point method to derive a proximal gradient method for minimizing \( f(x) : \text{prox}_f(x - \nabla f(x)) \). (We are not aware of any published optimization algorithms that have been constructed in this way.)

Using our software, it would be easy to detect such algorithm surgery by searching over all pairs (or trios, etc) of known algorithms. This combinatorial search is still not too expensive, since the list of known algorithms is still rather small, and the number of algorithms that makes up a monster algorithm is limited by the number of oracle calls at each iteration of the monster algorithm.
9. Algorithm conjugation. In this section, we introduce one last algorithm transformation, conjugation, which alters the oracle calls but results in algorithms that still bear a family resemblance.

In convex optimization, algorithm conjugation naturally relates some oracles to others [37, 38, §2]: for example, when $f^*(y) = \sup_x \{ x^Ty - f(x) \}$ is the Fenchel conjugate of $f$ [19, §3],

- $(\partial f)^{-1} = \partial f^*$, and
- Moreau’s identity. $I - \text{prox}_f = \text{prox}_{f^*}$.

We can rewrite any algorithm in terms of different, also easily computable, oracles using these identities. Consider a simple example: we will obfuscate the proximal gradient method (algorithm 9.1 [4, §10; 5]) by rewriting it in terms of the conjugate of the original oracle $\text{prox}_y$, using Moreau’s identity, as algorithm 9.2 [31].

| Algorithm 9.1 Proximal gradient method |
|----------------------------------------|
| for $k = 0, 1, 2, \ldots$ do |
| $x^{k+1} = \text{prox}_{tg}(x^k - t\nabla f(x^k))$ |
| end for |

| Algorithm 9.2 Conjugate of proximal gradient method |
|-----------------------------------------------|
| for $k = 0, 1, 2, \ldots$ do |
| $\xi^{k+1} = \xi^k - t\nabla f(\xi^k) - t\text{prox}_{\frac{1}{t}g^*}((\frac{1}{t}(\xi^k - t\nabla f(\xi^k)))$ |
| end for |

The transfer function of the algorithm changes when we rewrite the algorithm to call a different oracle, such as calling $\text{prox}_g$, instead of $\text{prox}_f$. Yet the sequence of states is preserved! Similarly, when we rewrite an algorithm to call $\partial f^*$ instead of $\partial f$, the resulting algorithm is related to the original algorithm by swapping the input and output sequences. We say that algorithm $B = C_nA$ is a conjugate of algorithm $A$ if algorithm $B$ results from rewriting algorithm $A$ to use the conjugates of the oracles in set $\kappa \subseteq [n]$, where $\nu = \{1, \ldots, n\}$ is the set of oracle indices for algorithm $A$. Interestingly, conjugation preserves the state sequence but not the oracle sequence. We will also call two algorithms conjugates if they are oracle-equivalent to a conjugate pair. Our goal in this section is to describe how to identify conjugate algorithms.

For simplicity in the remainder of this section, we suppose that all oracles are (sub)gradients. To detect equivalence of algorithms involving $\text{prox}$ using methods presented here, we may write the state-space realization of the algorithm in terms of (sub)gradients:

$$u = \text{prox}_f(y) \iff y \in u + \partial f(u).$$

In fact, our software uses this method to check algorithm conjugation. Restricting to (sub)gradients, we see from the identity $(\partial f)^{-1} = \partial f^*$ that algorithm conjugation swaps the input and output of an algorithm: the algorithm after conjugation takes the output of the original algorithm as input and produces the input of the original one as output. As shown in figure 6, the input sequence of the algorithm after conjugation is the original output sequence and the output sequence in the algorithm after conjugation is the original input sequence.

First, let’s introduce a bit of standard notation. Suppose an algorithm $A$ contains $n$ oracle calls in each iteration. The cardinality of a subset $\kappa \subseteq [n]$ is $|\kappa|$ and the complement is $\bar{\kappa} = [n] \setminus \kappa$. For any matrix $M \in \mathbb{R}^{n \times n}$, $M[\kappa, \nu]$ is the sub-matrix of $M$ whose rows and columns are indexed by $\kappa$ and $\nu \subseteq [n]$, respectively. We write $M[\kappa, \kappa]$ as $M[\kappa]$ for simplicity. For $i \in [n]$, the conjugation operator $C_i$ conjugates oracle $i$: it replaces the $i$th oracle by its inverse. The operator $C_\kappa$ conjugates all oracles in the set $\kappa \subseteq [n]$ to produce the conjugate algorithm $C_\kappa A$.  

![Fig. 6. Unrolled block-diagram representation of algorithm conjugation.](image-url)
Proposition 9.1. Suppose \( A \) has state-space realization \((A, B, C, D)\) and transfer function \( \hat{H}(z) \), and \( D[\kappa] \) is invertible. Then \( B \) is equivalent to \( C_\kappa A \) if and only if the transfer function \( \hat{H}'(z) \) of \( B \) satisfies

\[
(9.1) \quad P \hat{H}'(z) P^T = \begin{bmatrix}
\hat{H}[\kappa]^{-1}(z) & -\hat{H}[\kappa][\bar{\kappa}](z) \\
\hat{H}[\bar{\kappa}, \kappa](z)\hat{H}[\kappa]^{-1}(z) & \hat{H}[\bar{\kappa}, \bar{\kappa}](z) - \hat{H}[\bar{\kappa}, \kappa](z)\hat{H}[\kappa]^{-1}(z)\hat{H}[\kappa, \bar{\kappa}](z)
\end{bmatrix}.
\]

Here \( P \) is a permutation matrix that swaps rows and columns so indices in \( \kappa \) come first:

\[
(9.2) \quad P \hat{H}(z) P^T = \begin{bmatrix}
\hat{H}[\kappa](z) & \hat{H}[\bar{\kappa}, \kappa](z) \\
\hat{H}[\bar{\kappa}, \kappa](z) & \hat{H}[\bar{\kappa}, \bar{\kappa}](z)
\end{bmatrix}.
\]

Proof. Sufficiency. Without loss of generality, suppose the oracles \( \kappa = \{1, \ldots, |\kappa|\} \) appear first,

\[
\hat{H}(z) = \begin{bmatrix}
\hat{H}[\kappa](z) & \hat{H}[\bar{\kappa}, \kappa](z) \\
\hat{H}[\bar{\kappa}, \kappa](z) & \hat{H}[\bar{\kappa}, \bar{\kappa}](z)
\end{bmatrix}, \quad D = \begin{bmatrix}
D[\kappa] & D[\bar{\kappa}, \kappa] \\
D[\bar{\kappa}, \kappa] & D[\bar{\kappa}, \bar{\kappa}]
\end{bmatrix},
\]

and consequently the permutation matrix \( P \) is the identity. We obtain the desired results from (4.14) by setting \( D_{11} = D[\kappa] \), \( H_{11}(z) = \hat{H}[\kappa](z) \), \( H_{12}(z) = \hat{H}[\kappa, \bar{\kappa}](z) \), \( H_{21}(z) = \hat{H}[\bar{\kappa}, \kappa](z) \), and \( H_{22}(z) = \hat{H}[\bar{\kappa}, \bar{\kappa}](z) \).

Necessity is provided by proposition 6.1 as the transfer function uniquely characterizes an equivalence class of algorithms.

From proposition 9.1, the transfer function \( \hat{H}(z) \) of algorithm \( A \) is partially inverted when the algorithm is conjugated by \( C_\kappa \). The new transfer function \( \hat{H}'(z) \) results from applying the Sweep operator with indices \( \kappa \) to \( \hat{H}(z) \) [22, 43]. If we consider the input and output sequences for each oracle separately, for any oracle in \( \kappa \), the input sequence corresponding to \( C_\kappa A \) is the original input sequence in \( A \) and the output sequence corresponding to \( C_\kappa A \) is the original output sequence in \( A \). The input and output sequences of oracles in \( [n] \setminus \kappa \) remain unchanged in the new algorithm \( C_\kappa A \). Here, assumption 5.3 ensures the algorithms compared call either same oracles or their corresponding conjugate oracles and in each iteration the number of oracle calls are the same.

Proposition 9.1 assumes that \( D[\kappa] \) is invertible. In fact, \( C_\kappa A \) is a causal algorithm if and only if \( D[\kappa] \) is invertible. We need not condition on causality in the proposition, since any algorithm that can be written down as a set of update equations is necessarily causal.

Now we consider two special cases: conjugating 1) a single oracle, or 2) all of the oracles.

Corollary 9.2. Consider algorithm \( A \) with state-space realization \((A, B, C, D)\) and transfer function \( \hat{H}(z) \in \mathbb{R}^{n \times n} \).

(a) Suppose \( D_{kk} \neq 0 \) for any \( k \in [n] \). Then the new transfer function \( \hat{H}'(z) \) of \( C_k A \) can be expressed entrywise as

\[
(9.3) \quad h'_{ij}(z) = \begin{cases}
1/h_{kk}(z) & i = k, \ j = k \\
th_{kj}(z)/h_{kk}(z) & i = k, \ j \neq k \\
h_{ik}(z)/h_{kk}(z) & i \neq k, \ j = k \\
h_{ij}(z) - h_{ik}(z)h_{kj}(z)/h_{kk}(z) & i \neq k, \ j \neq k,
\end{cases}
\]

as \( h_{ij}(z) \) and \( h'_{ij}(z) \) \( 1 \leq i, j \leq n \) denote the entries of \( \hat{H}(z) \) and \( \hat{H}'(z) \) respectively.

(b) Suppose \( D \) is invertible. Then the transfer function \( \hat{H}'(z) \) of \( C_{[n]} A \) satisfies \( \hat{H}'(z) = \hat{H}^{-1}(z) \).

Proximal gradient. Now we can revisit algorithms 9.1 and 9.2 and show that they are conjugate. The transfer functions of algorithms 9.1 and 9.2 are computed as \( \hat{H}_{14}(z) \) and \( \hat{H}_{15}(z) \) below. Note that the state-space realizations are written in terms of (sub)gradients. From corollary 9.2, they are conjugate with respect to the second oracle.

\[
\hat{H}_{14}(z) = \begin{bmatrix}
-\frac{1}{z^2 + \frac{1}{4}} & -\frac{1}{2z + \frac{1}{4}} \\
-\frac{1}{2z + \frac{1}{4}} & -\frac{1}{z^2 + \frac{1}{4}}
\end{bmatrix}, \quad \hat{H}_{15}(z) = \begin{bmatrix}
0 & \frac{1}{z^2 - \frac{1}{4}} \\
-1 & -\frac{1}{z^2 + \frac{1}{4}}
\end{bmatrix}
\]


For simplicity, detailed proof is provided in appendix K. Intuitively, as we invert the input-output map of restriction in section 10.

Below as \( \hat{C} \), a permutation and conjugation (in either order, as they commute), with a different choice of parameters:

see proposition L.1 and proof in appendix L.

choices of parameters of algorithms can lead to different relations between algorithms.

can be illustrated as follows. Recall \( \hat{\kappa} \) function of this special parameterization of ADMM is shown as \( \hat{\kappa} \), as the order of the oracles in \( \kappa \) set

Diagonal of \( C \) conjugate operator. (These subgradient oracles are used for the analysis but need not be computed explicitly.)

All these subgradient oracles are associated with proximal operators, and so they are unique-valued, even though subgradients are generally set-valued: the input-output pairs match those returned by the proximal operator. (These subgradient oracles are used for the analysis but need not be computed explicitly.)

The fixed points of an algorithm and its conjugate are related as stated in proposition 9.3. Note that entries above diagonal of \( D \) are all zero because \( \mathcal{A} \) is causal. Thus, \( \det(D[\{ij\}]) = D_{ii}D_{jj} \neq 0 \) and \( C_{ij}\mathcal{A} \) is causal. The commutative property of the Sweep operator gives the result \( C_{ij}\mathcal{A} = C_{ji}\mathcal{A} = C_{ij}\mathcal{A} [22, 43] \).}

PROPOSITION 9.4. Suppose algorithm \( \mathcal{A} \) has state-space realization \( (A, B, C, D) \), where \( D_{ii} \neq 0 \) and \( D_{jj} \neq 0 \). Then \( C_{ij}\mathcal{A} = C_{ji}\mathcal{A} = C_{ij}\mathcal{A} \).

Proof. By corollary 9.2, if \( D_{ii} \neq 0 \) and \( D_{jj} \neq 0 \), then \( C_{ij}\mathcal{A} \) and \( C_{ji}\mathcal{A} \) are causal. Note that entries above diagonal of \( D \) are all zero because \( \mathcal{A} \) is causal. Thus, \( \det(D[\{ij\}]) = D_{ii}D_{jj} \neq 0 \) and \( C_{ij}\mathcal{A} \) is causal. The commutative property of the Sweep operator gives the result \( C_{ij}\mathcal{A} = C_{ji}\mathcal{A} = C_{ij}\mathcal{A} \).

DR and Chambolle-Pock. Another important example is the relation between DR (algorithm 7.5) and the primal-dual optimization method proposed by Chambolle and Pock (algorithm 9.3 [11; 33]). Note that algorithm 7.5 has parameter \( t \) and linear operator \( L \), and algorithm 9.3 has parameters \( \tau \) and \( \sigma \) and linear operator \( M \). Let \( M = L \) so that algorithms 7.5 and 9.3 solve the same problem. Further suppose that \( M \) is invertible and \( MMT^T = \delta I \) for any \( \delta > 0 \). By corollary 9.2, we know that they are conjugate with respect to the second oracle if \( \tau = t \) and \( \sigma = 1/(\delta t) \). So DR and the Chambolle-Pock method (when the parameter value \( \tau = t \) and \( \sigma = 1/(\delta t) \)) are conjugate. The transfer functions of algorithms 7.5 and 9.3 are provided below as \( \hat{H}_{10}(z) \) and \( H_{16}(z) \) respectively. We will say more about how to discover the correct parameter restriction in section 10.

\[
\hat{H}_{10}(z) = \left[ \begin{array}{c}
\frac{-I}{t(1-2z)} L^T & -\frac{L}{z-1} L^T \\
-\frac{L}{z-1} L^T & \frac{I}{t(1-2z)} L^T 
\end{array} \right], \quad \hat{H}_{16}(z) = \left[ \begin{array}{c}
\frac{H}{z-1} L^T (LL^T)^{-1} L & \frac{L}{z-1} L^T (LL^T)^{-1} \\
\frac{H}{z-1} L^T (LL^T)^{-1} L & \frac{L}{z-1} L^T (LL^T)^{-1} 
\end{array} \right]
\]

In order to test equivalence, all algorithms must use the same set of oracles. This requirement becomes tricky when algorithms are written in terms of an argmin: what is the oracle? To resolve this issue, we compute the space-state realization of every algorithm in this section using the subgradient as the oracle. All these subgradient oracles are associated with proximal operators, and so they are unique-valued, even though subgradients are generally set-valued: the input-output pairs match those returned by the proximal operator. (These subgradient oracles are used for the analysis but need not be computed explicitly.)

The fixed points of an algorithm and its conjugate are related as stated in proposition 9.3.

PROPOSITION 9.3. If an algorithm \( \mathcal{A} \) converges to a fixed point \( (y[\kappa]*, y[\tilde{\kappa}]*, u[\kappa]*, u[\tilde{\kappa}]*, x*) \), then its conjugate \( \hat{\mathcal{C}}_\kappa \mathcal{A} \) converges to fixed point \( (u[\kappa]*, y[\tilde{\kappa}]*, y[\kappa]*, u[\tilde{\kappa}]*, x*) \).

For simplicity, detailed proof is provided in appendix K. Intuitively, as we invert the input-output map of \( u[\kappa] \) and \( y[\kappa] \), the corresponding parts in the fixed point are also inverted.

DR and ADMM. We showed in subsection 7.3 that the DR (algorithm 7.5) and ADMM (algorithm 7.6) are related by permutation with a certain choice of parameters. Here, we show that they are related by permutation and conjugation (in either order, as they commute), with a different choice of parameters: \( A = L^T, B = I, c = 0, \rho = t \) for ADMM. Further suppose that linear operator \( L \) is invertible. The transfer function of this special parameterization of ADMM is shown as \( \hat{H}_{17}(z) \). Relations between DR and ADMM can be illustrated as follows. Recall \( \hat{H}_{10}(z) \) is the transfer function of DR. Here we can observe that different choices of parameters of algorithms can lead to different relations between algorithms.

\[
\hat{H}_{17}(z) = \left[ \begin{array}{c}
\frac{-I}{t(1-2z)} L^{-1} L^T & -\frac{L}{z-1} L^{-1} L^T \\
-\frac{L}{z-1} L^{-1} L^T & \frac{I}{t(1-2z)} L^{-1} L^T 
\end{array} \right] \rightarrow \left[ \begin{array}{c}
\frac{-I}{t(1-2z)} L^{-1} L^T & -\frac{L}{z-1} L^{-1} L^T \\
-\frac{L}{z-1} L^{-1} L^T & \frac{I}{t(1-2z)} L^{-1} L^T 
\end{array} \right] \rightarrow \hat{H}_{10}(z)
\]

The commutative property is important to identify relations between algorithms efficiently. For example, suppose we would like to identify the relations between algorithms 7.5 and 7.6, with transfer functions \( \hat{H}_{10}(z) \) and \( \hat{H}_{17}(z) \). We can first perform conjugation and next permutation on algorithm 7.5, and then test...
equivalence between the resulting algorithm and algorithm 7.6. We need not try permutation followed by conjugation; as these commute, both orders lead to the same transfer function.

We have already shown several relations between DR (algorithm 7.5), ADMM (algorithm 7.6), and the Chambolle-Pock method (algorithm 9.3) using conjugation and permutation. We represent these relations in figure 7. The figure relates 8 different algorithms: Starting from DR, since it contains 2 oracles, there are 2 possible different algorithms by permutation. From the state-space realization, we can conjugate both oracles, which yields 4 different algorithms by conjugation of different oracles. Therefore, in total there are $2 \times 4 = 8$ possible different algorithms, including both ADMM and Chambolle-Pock. In the figure, $C_1$ and $C_2$ denote conjugation with respect to the first and second oracles respectively, $P$ denotes permutation, and we can move between algorithms by applying the transformation on each edge, in either direction, as each transformation is an involution.

![Fig. 7. Connections between DR, ADMM, and Chambolle-Pock method.](image)

10. Linnaeus. We have presented a framework for detecting equivalence between iterative algorithms for continuous optimization. In this section, we briefly introduce a software package called LINNAEUS that implements these ideas. The implementation and documentation are available at https://github.com/udellgroup/Linnaeus_software. More detailed information can be found in appendix A.

The input is an algorithm described in user-friendly syntax with variables, parameters, functions, oracles, and update equations. The system will automatically translate the input algorithm into a canonical form (the transfer function) and use the canonical form to identify whether the algorithm is equivalent to any reference algorithm, possibly after transformations such as permutation, conjugation, or repetition. All expressions in LINNAEUS are defined symbolically, using the python package for symbolic mathematics sympy.

Given two input algorithms, LINNAEUS computes the transfer functions and can compare them to detect equivalence and other relations. Some algorithms are equivalent or related only when the parameters satisfy a certain condition: for example, DR and ADMM. If the transfer functions of each algorithm use different parameters, LINNAEUS form symbolic equations and solve the equations to determine conditions that, if satisfied by the algorithm parameters, yield the desired relation between the algorithms; see (6.5) in section 6.

This package can be used by researchers (or peer reviewers) who wish to understand the novelty of new algorithmic ideas and connections to existing algorithms. Further, the software can also serve as a search engine, which will identify connections from the input algorithm to existing algorithms in the literature that appear in LINNAEUS’s algorithm library.

11. Conclusion and future work. In this paper, we have presented a framework for reasoning about equivalence between a broad class of iterative algorithms by using ideas from control theory to represent optimization algorithms. The main insight is that by representing an algorithm as a linear dynamical system in feedback with a static nonlinearity, we can recognize equivalent algorithms by detecting algebraic relations between the transfer functions of the associated linear systems. This framework can identify algorithms that result in the same sequence of oracle calls, or algorithms that are the same up to shifts of the update equations, repetition of the updates with the same unit block, and conjugation of the function oracles. These
ideas are implemented in the software package Linnaeus, which allows researchers to search for algorithms that are related to a given input and identify parameter settings that make the algorithms equivalent. Our goal is to allow researchers add new algorithms to Linnaeus as they are developed, so that Linnaeus can remain a valuable resource for algorithm designers seeking to understand connections (if any) to previous methods.

Our framework requires that the algorithm is linear in the state and oracle outputs, but not necessarily in the parameters. This constraint still allows us to handle a surprisingly large class of algorithms. There are several interesting directions for future work.

Can we detect equivalence between stochastic or randomized algorithms? Our framework applies to such algorithms with almost no modifications, simply by allowing random oracles. For example, we can accept oracles like random search argmin \{f(x + \omega_i) : i = 1, \ldots, k\}, stochastic gradient \nabla_f(x + \omega), or noisy gradient \nabla f(x + \omega). The definition of oracle equivalence would need a slight modification: for algorithms that use (pseudo-)randomized oracles, two algorithms are oracle-equivalent if they generate identical sequences of oracle calls given the same random seed.

Can we detect equivalence between parallel or distributed algorithms? Surprisingly, our framework still works for parallel or distributed algorithms. Notice that in a parallel algorithm, many oracle calls may be independently executed on different processors at about the same time. The precise ordering of these calls is not determined by the algorithm, and so different runs of the algorithm can generate different oracle sequences. However, all the possible oracle sequences generated by the same algorithm share the same dependence graph. Using the formalism defined in subsection 7.1, we can see that our framework can identify equivalence between parallel or distributed algorithms using the expanded definition of oracle equivalence: two algorithms are oracle-equivalent if there exists a way of writing each algorithm as a sequence of updates so that they generate identical sequences of oracle calls.

Can we detect equivalence between adaptive or nonlinear algorithms? Transfer functions are only defined for linear time-invariant (LTI) systems, so the LTI assumption in our framework is critical. Nevertheless, many of the other concepts from subsection 4.3 do extend to systems that are almost LTI. For example, an algorithm with parameters that change on a fixed schedule but is otherwise linear, such as gradient descent with a diminishing stepsize, can be regarded as a linear time-varying (LTV) system [3], and the notion of a transfer function has been generalized to LTV systems [26]. If, instead, the parameters change adaptively based on the other state variables, the system can be regarded as a linear parameter varying (LPV) system [30] or a switched system [42]. Examples of such algorithms include nonlinear conjugate gradient methods and quasi-Newton methods.

For these more complicated cases, it is still reasonable to ask whether two algorithms invoke the same sequence of oracle calls. Discovering representations for nonlinear or time-varying algorithms that suffice to check equivalence is an interesting direction for future research.

REFERENCES

[1] Awesome gpt-3. https://github.com/elyase/awesome-gpt3, 2020.
[2] Openai api. https://beta.openai.com/, 2020.
[3] P. J. Antsaklis and A. N. Michel, Linear systems, Birkhäuser, 2006.
[4] A. Beck, First-order methods in optimization, SIAM, 2017.
[5] A. Beck and M. Teboulle, A fast iterative shrinkage-thresholding algorithm for linear inverse problems, SIAM Journal on Imaging Sciences, 2 (2009), pp. 183–202.
[6] S. Boyd, N. Parikh, E. Chu, B. Peleato, and J. Eckstein, Distributed optimization and statistical learning via the alternating direction method of multipliers, Foundations and Trends in Machine Learning, 3 (2011), pp. 1–122.
[7] S. Boyd and L. Vandenberghe, Convex optimization, Cambridge University Press, 2004.
[8] T. Brown, B. Mann, N. Ryder, M. Subbiah, J. D. Kaplan, P. Dhariwal, A. Neelakantan, P. Shyam, G. Sastry, A. Askell, S. Agarwal, A. Herbert-Voss, G. Krueger, T. Henighan, R. Child, A. Ramesh, D. Ziegler, J. Wu, C. Winter, C. Hesse, M. Chen, E. Sigler, M. Litwin, S. Gray, B. Chess, J. Clark, C. Berner, S. McCandlish, A. Radford, I. Sutskever, and D. Amodei, Language models are few-shot learners, in Advances in Neural Information Processing Systems, vol. 33, 2020, pp. 1877–1901.
[9] S. Bubeck, Convex optimization: algorithms and complexity, Foundations and Trends® in Machine Learning, 8 (2015), pp. 331–357.
[10] Y. Censor, A. Gibali, and S. Reich, The subgradient extragradient method for solving variational inequalities in hilbert space, Journal of Optimization Theory and Applications, 148 (2011), pp. 318–335.
[11] A. Chambolle and T. Pock, A first-order primal-dual algorithm for convex problems with applications to imaging, Journal of mathematical imaging and vision, 40 (2011), pp. 120–145.
Appendix A. Linnaeus. In this section, we introduce our software package called Linnaeus that implements these ideas in detail. This package can be used by researchers (or peer reviewers) who wish to understand the novelty of new algorithmic ideas and connections to existing algorithms. The input is an algorithm described in user-friendly syntax with variables, parameters, functions, oracles, and update equations. The system will automatically translate the input algorithm into a canonical form (the transfer function) and use the canonical form to identify whether the algorithm is equivalent to any reference algorithm, possibly after transformations such as permutation, conjugation, or repetition. Further, the software can also serve as a search engine, which will identify connections from the input algorithm to existing algorithms in the literature that appear in Linnaeus’s algorithm library.

A.1. Illustrative examples. We use Linnaeus to identify the relations between algorithms presented previously in the paper. These examples demonstrate the power and simplicity of Linnaeus. Code for these examples can be found at https://github.com/udellgroup/Linnaeus_software.

Algorithms 3.1 and 3.2. The following code identifies that algorithms 3.1 and 3.2 are oracle-equivalent. We input algorithms 3.1 and 3.2 with variables, oracles, and update equations, and parse them into state-space realizations. Then we check oracle equivalence using the function is_equivalent. The system returns True, consistent with our analytical results in sections 3 and 6.

```
# define Algorithm 3.1
algo1 = Algorithm("Algorithm 3.1")

# add oracle gradient of f to Algorithm 3.1
gadf = algo1.add_oracle("gradf")

# add variables x1, x2, and x3 to Algorithm 3.1
x1, x2, x3 = algo1.add_var("x1", "x2", "x3")

# add update equations
# x3 <- 2x1 - x2
algo1.add_update(x3, 2*x1 - x2)
# x2 <- x1
algo1.add_update(x2, x1)
# x1 <- x3 - 0.1*gradf(x3)
algo1.add_update(x1, x3 - 1/10*gradf(x3))

# parse Algorithm 3.1, translate it into canonical form
algo1.parse()

------------------------------------------------------------
Parse Algorithm 3.1:
x_3 ← 2x_1 - x_2
x_2 ← x_1
x_1 ← x_3 - 0.1gradf(x_3)
------------------------------------------------------------
```

```
# define Algorithm 3.2
algo2 = Algorithm("Algorithm 3.2")

xi1, xi2, xi3 = algo2.add_var("xi1", "xi2", "xi3")
gadf = algo2.add_oracle("gradf")

# xi3 <- xi1
algo2.add_update(xi3, xi1)
# xi1 <- xi1 - xi2 - 1/5*gradf(xi1)
algo2.add_update(xi1, xi1 - xi2 - 1/5*gradf(xi1))
# xi2 <- xi2 + 1/10*gradf(xi3)
algo2.add_update(xi2, xi2 + 1/10*gradf(xi3))
```

26
Parse Algorithm 3.2:
\[ \xi_3 \leftarrow \xi_1 \]
\[ \xi_1 \leftarrow \xi_1 - \xi_2 - 0.2\text{gradf}(\xi_3) \]
\[ \xi_2 \leftarrow \xi_2 + 0.1\text{gradf}(\xi_3) \]

# check oracle equivalence
lin.is_equivalent(algo1, algo2, verbose = True)

Algorithm 3.1 is equivalent to Algorithm 3.2.
True

**Algorithms 3.5 and 3.6.** The second example identifies that algorithms 3.5 and 3.6 are shift-equivalent. We input and parse the algorithms into state-space realizations and then check shift equivalence (cyclic permutation) using the function `is_permutation`. The system returns `True`, consistent with results in sections 3 and 7.

```
algo5 = Algorithm("Algorithm 3.5")
x1, x2, x3 = algo5.add_var("x1", "x2", "x3")
proxf, proxg = algo5.add_oracle("proxf", "proxg")

# x1 <- proxf(x3)
algo5.add_update(x1, proxf(x3))
# x2 <- proxg(2x1 - x3)
algo5.add_update(x2, proxg(2*x1 - x3))
# x3 <- x3 + x2 - x1
algo5.add_update(x3, x3 + x2 - x1)

algo5.parse()
```

Parse Algorithm 3.5:
\[ x_1 \leftarrow \text{proxf}(x_3) \]
\[ x_2 \leftarrow \text{proxg}(2x_1 - x_3) \]
\[ x_3 \leftarrow x_3 + x_2 - x_1 \]

```
algo4 = Algorithm("Algorithm 3.6")
xi1, xi2 = algo4.add_var("xi1", "xi2")
proxf, proxg = algo4.add_oracle("proxf", "proxg")

# xi1 <- proxg(-xi1 + 2*xi2) + xi1 - xi2
algo4.add_update(xi1, proxg(-xi1 + 2*xi2) + xi1 - xi2)
# xi2 <- proxf(xi1)
algo4.add_update(xi2, proxf(xi1))

algo4.parse()
```

Parse Algorithm 3.6:
\[ \xi_1 \leftarrow \text{prox}_g(-\xi_1 + 2\xi_2) + \xi_1 - \xi_2 \]
\[ \xi_2 \leftarrow \text{prox}_f(\xi_1) \]

```
# check cyclic permutation (shift equivalence)
lin.is_permutation(algo5, algo6, verbose = True)
```

Algorithm 3.5 is a permutation of Algorithm 3.6.

True

**DR and ADMM.** The third illustrative example shows that DR and ADMM are related by permutation and conjugation, as we saw in section 9. Further, LINNAEUS can even reveal the specific parameter choice required for the relation to hold. Just as in section 9, suppose both DR and ADMM solve problem (4.1) with \( A = L^T \), \( B = I \), and \( c = 0 \). We input and parse DR and ADMM. To detect the relations, we use function `test_conjugate_permutation` to check conjugation and permutation between DR and ADMM. The results are the same as section 9.

```python
DR = Algorithm("Douglas-Rachford splitting")
x1, x2, x3 = DR.add_var("x1", "x2", "x3")
t = DR.add_parameter("t")
L = DR.add_parameter("L", commutative = False)
# x1 <- prox_tf(x3)
DR.add_update(x1, lin.prox(f, t)(x3))
# x2 <- prox_tgL(2x1 - x3)
DR.add_update(x2, lin.prox(g, t, L)(2*x1 - x3))
# x3 <- x3 + x2 - x1
DR.add_update(x3, x3 + x2 - x1)
DR.parse()
```

Parse Douglas-Rachford splitting:
\[ x_1 \leftarrow \text{prox}_f(x_3) \]
\[ x_2 \leftarrow \text{prox}_{t_g L}(2x_1 - x_3) \]
\[ x_3 \leftarrow x_3 + x_2 - x_1 \]

```
ADMM = Algorithm("ADMM")
f, g = ADMM.add_function("f", "g")
rho = ADMM.add_parameter("rho")
L = ADMM.add_parameter("L", commutative = False)
x1i, x2i, x3i = ADMM.add_var("x1i", "x2i", "x3i")

# x1i <- argmin(x1i, g^*(x1i) + 1/2*rho*||T(L)x1i + x2i + x3i||^2)
ADMM.add_update(x1i, lin.argmin(x1, g(x1i) + 1/2*rho*lin.norm_square(T(L)*x1i + x2i + x3i)))
# x2i <- argmin(x2i, f^*(x2i) + 1/2*rho*||T(L)x1i + x2i + x3i||^2)
ADMM.add_update(x2i, lin.argmin(x1, f(x2i) + 1/2*rho*lin.norm_square(T(L)*x1i + x2i + x3i)))
# x3i <- x3i + T(L)x1i + x2i
ADMM.add_update(x3i, x3i + T(L)*x1i + x2i)
ADMM.parse()
```
Parse ADMM:
\[
\begin{align*}
\xi_1 &\leftarrow \text{argmin}_{\xi_1} \{ g(\xi_1) + 0.5 \rho \text{norm}^2 (T(L)\xi_1 + \xi_2 + \xi_3) \} \\
\xi_2 &\leftarrow \text{argmin}_{\xi_2} \{ f(\xi_2) + 0.5 \rho \text{norm}^2 (T(L)\xi_1 + \xi_2 + \xi_3) \} \\
\xi_3 &\leftarrow T(L)\xi_1 + \xi_2 + \xi_3
\end{align*}
\]

# check permutation and conjugation
# between DR and ADMM
lin.test_conjugate_permutation(DR, ADMM)

---

A.2. Implementation. In this subsection, we briefly describe the implementation of Linnaeus. All expressions in Linnaeus are defined symbolically, using the python package for symbolic mathematics sympy. In Linnaeus, an algorithm is specified by defining variables, parameters, functions, oracles, and update equations. All variables and parameters are symbolic, so there is no need to specialize problem dimensions or parameter choices. The system automatically translates an input algorithm into its state-space realization and computes the transfer function. The transfer functions can be compared and manipulated as needed to establish various kinds of equivalences or other relations between algorithms.

Parameter declaration. Parameters of the algorithm can be declared as scalar (commutative) or vector or matrix (noncommutative). The following code shows how to add scalar \( t \) and matrix \( L \) to algo1.

```python
# add a scalar parameter t
t = algo1.add_parameter("t")
# add a matrix parameter L
L = algo1.add_parameter("L", commutative = False)
```

Parameter specification. Given two input algorithms, Linnaeus computes the transfer functions and can compare them to detect equivalence and other relations. Some algorithms are equivalent or related only when the parameters satisfy a certain condition: for example, DR and ADMM. If the transfer functions of each algorithm use different parameters, Linnaeus form symbolic equations and solve the equations to determine conditions that, if satisfied by the algorithm parameters, yield the desired relation between the algorithms; see (6.5) in section 6.

Oracles and function. Oracles play the starring role in our framework: oracle equivalence is possible only if two algorithms share the same oracles. In Linnaeus, we provide two approaches to declare and add oracles to an algorithm. The black-box approach is to define oracles as black boxes. When parsing the algorithm, the system treats each oracle as a distinct entity unrelated to any other oracle. An oracle declared using syntax add_oracle uses the black-box approach. For example, we may add oracles \( \nabla f \) and prox \( g \) to algorithm algo1:

```python
# add oracle gradient of f in the first approach
gradf = algo1.add_oracle("gradf")
# add oracle prox of g in the first approach
proxg = algo1.add_oracle("proxg")
```
The functional approach is to define oracles in terms of the (sub)gradient of a function. When parsing an algorithm, all the oracles will be decomposed into (sub)gradients and the state-space realization given in terms of (sub)gradients. We say that two algorithms are oracle-equivalent in terms of functional oracles if they are oracle-equivalent after rewriting the algorithm to use only (sub)gradient oracles. This approach is critical to allow us to identify algorithm conjugation, since conjugate algorithms use different (conjugate) oracles. If every algorithm is represented in terms of (sub)gradients, algorithm conjugation can be detected using proposition 9.1. Fortunately, common oracles such as prox and argmin can be easily written in terms of (sub)gradients: for example, \( \text{prox}_f(x) = (I - \partial f)^{-1}(x) \) and argmin as (A.1).

To use the functional approach, users must define and add functions to the algorithm first using `add function` and then declare and add oracles. The following code shows how to use the functional approach to declare and add oracles \( \nabla f \) and \( \text{prox}_f \).

```plaintext
# add function f
f = algo1.add_function("f")
# gradient of f with respect to x1
lin.grad(f)(x1)
# prox of f with respect to x2 and parameter t
lin.prox(f,t)(x2)
```

A.3. Black-box vs functional oracles. Are two algorithms equivalent with respect to black-box oracles if and only if they are equivalent with respect to functional oracles? Intuitively, when oracles are defined in terms of (sub)gradients, it might be possible to identify more relations with other algorithms. However, as stated in proposition A.1, for algorithms that use only proximal operators, argmins, and (sub)gradients as oracles, equivalence is preserved under both black-box and functional definitions of oracles.

**Proposition A.1.** Suppose two algorithms use only proximal operators, argmins, and (sub)gradients as oracles. Then the two algorithms are equivalent with respect to black-box oracles if and only if they are also equivalent with respect to functional oracles.

**Proof.** Since for any function \( g \) and any \( t \), \( \text{prox}_{tg}(x) = \arg\min_y \{ tg(y) + \frac{1}{2}\|x - y\|^2 \} \), we can treat proximal operator as a special case of argmin. Without loss of generality, any argmin oracle in a linear algorithm has the form

\[
    z = \arg\min_x \left\{ \lambda g(x) + \frac{1}{2} \begin{bmatrix} x & y \end{bmatrix}^T \begin{bmatrix} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \right\}.
\]

Here \( z \) is the value of the oracle and \( y \) can be regarded as the argument, which means from the perspective of a linear system, \( z \) is the input and \( y \) is the output. The parameter \( \lambda \) can be a scalar or matrix, \( g \) is a function, and \( Q_{11}, Q_{12}, Q_{21}, Q_{22} \) are parameter matrices. Specifically,

\[
    \begin{bmatrix} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \end{bmatrix}
\]

is a symmetric matrix and

\[
    \frac{1}{2} \begin{bmatrix} x \\ y \end{bmatrix}^T \begin{bmatrix} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}
\]

is a quadratic term with respect to \( x \) and \( y \). The matrix \( Q_{11} \) must be invertible if the argmin oracle is single-valued. To recover the proximal operator, choose a scalar \( \lambda \) and set

\[
    \begin{bmatrix} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \end{bmatrix} = \begin{bmatrix} I & -I \\ -I & I \end{bmatrix}.
\]

If \( g \) is a convex function, the argmin oracle can be written in terms of the subgradient oracle \( \partial g \) as follows,

(A.1) \[
    z \in -Q_{11}^{-1}\lambda \partial g(z) - Q_{11}^{-1}Q_{12}y.
\]
Suppose we have an algorithm with \( n + m \) oracles in total, consisting of \( n \) arguments and \( m \) (sub)gradients. We can group the arguments and the (sub)gradients together respectively and partition the state-space realization accordingly as

\[
\begin{bmatrix}
A & B_1 & B_2 \\
C_1 & D_{11} & D_{12} \\
C_2 & D_{21} & D_{22}
\end{bmatrix},
\]

where \( C_1 \), \( B_1 \) correspond to the arguments, \( C_2 \), \( B_2 \) correspond to the (sub)gradients, and \( D \) is partitioned accordingly into \( D_{11} \), \( D_{12} \), \( D_{21} \), and \( D_{22} \). The transfer function can be represented accordingly as

\[
\hat{H}(z) = \begin{bmatrix}
\hat{H}_{11}(z) & \hat{H}_{12}(z) \\
\hat{H}_{21}(z) & \hat{H}_{22}(z)
\end{bmatrix} = \begin{bmatrix}
C_1(zI - A)^{-1}B_1 + D_{11} & C_1(zI - A)^{-1}B_2 + D_{12} \\
C_2(zI - A)^{-1}B_1 + D_{21} & C_2(zI - A)^{-1}B_2 + D_{22}
\end{bmatrix}.
\]

The input and output are partitioned as \((\bar{u}, \tilde{u})\) and \((\bar{y}, \tilde{y})\), where \(\bar{y} = (y_1, \ldots, y_n)\), \(\tilde{y} = (y_{n+1}, \ldots, y_{n+m})\), \(\tilde{u}_1 = (z_1, \ldots, z_n)\), and \(\tilde{u}_2 = (\nabla f_{n+1}(y_{n+1}), \ldots, \nabla f_{n+m}(y_{n+m}))\). For each \(i \in \{1, \ldots, n\}\) we have

\[
z_i = \arg\min_x \left\{ \lambda_i f_i(x) + \frac{1}{2} \begin{bmatrix} x \\ y_i \end{bmatrix}^T \begin{bmatrix} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \end{bmatrix} \begin{bmatrix} x \\ y_i \end{bmatrix} \right\}
\]

where \(Q_{11}\) is invertible for any \(i \in \{1, \ldots, n\}\).

Now we rewrite the linear system so that the nonlinearities corresponding to the arguments for the new linear system are (sub)gradients. Let \(\lambda = \text{diag}(\lambda_1, \ldots, \lambda_n)\), \(Q_1 = \text{diag}(Q_{11}, \ldots, Q_{1n})\), \(Q_2 = \text{diag}(Q_{12}, \ldots, Q_{2n})\), and \(M_1 = Q^{-1}_1 \lambda\). The new state-space realization in terms of the (sub)gradient oracles is

\[
\begin{bmatrix}
A - B_1(I + M_1D_{1i})^{-1}M_1C_1 & \cdots & -B_1(I + M_1D_{1i})^{-1}M_1C_2 - B_2(I + M_1D_{11})^{-1}M_1D_{12} \\
\cdots & \cdots & \cdots \\
C_2 - D_{21}(I + M_1D_{11})^{-1}M_1C_1 & \cdots & -D_{21}(I + M_1D_{11})^{-1}M_1C_2 - D_{22}(I + M_1D_{11})^{-1}M_1D_{12}
\end{bmatrix}.
\]

We can compute the transfer function as

\[
\hat{H}'(z) = \begin{bmatrix}
\hat{H}'_{11}(z) & \hat{H}'_{12}(z) \\
\hat{H}_{21}(z) & \hat{H}_{22}(z)
\end{bmatrix} = \begin{bmatrix}
-(I + M_1\hat{H}_{11}(z))^{-1}M_2 & -(I + M_1\hat{H}_{11}(z))^{-1}M_1\hat{H}_{12}(z) \\
-\hat{H}_{21}(z)(I + M_1\hat{H}_{11}(z))^{-1}M_2 & \hat{H}_{22}(z) - \hat{H}_{21}(z)(I + M_1\hat{H}_{11}(z))^{-1}M_1\hat{H}_{12}(z)
\end{bmatrix}.
\]

Note that \(I + M_1D_{11}\) is invertible (otherwise the algorithm is not causal) and consequently \(I + M_1\hat{H}_{11}(z)\) is invertible. The matrix \(Q_1\) is also invertible, since \(Q_{11}\) is invertible for any \(i \in \{1, \ldots, n\}\). A detailed proof of (A.4) and (A.5) is provided in appendix M. Therefore, we know that if \(\hat{H}(z)\) is fixed then \(\hat{H}'(z)\) is also fixed.

Appendix B. Proof of (4.14). Since \(u\) and \(y\) are partitioned as \(u = (u_1, u_2)\) and \(y = (y_1, y_2)\), the state-space realization can be partitioned accordingly as

\[
\begin{bmatrix}
A & B_1 & B_2 \\
C_1 & D_{11} & D_{12} \\
C_2 & D_{21} & D_{22}
\end{bmatrix}.
\]

We can express the transfer function \(\hat{H}(z)\) as

\[
\hat{H}(z) = \begin{bmatrix}
\hat{H}_{11}(z) & \hat{H}_{12}(z) \\
\hat{H}_{21}(z) & \hat{H}_{22}(z)
\end{bmatrix} = \begin{bmatrix}
C_1(zI - A)^{-1}B_1 + D_{11} & C_1(zI - A)^{-1}B_2 + D_{12} \\
C_2(zI - A)^{-1}B_1 + D_{21} & C_2(zI - A)^{-1}B_2 + D_{22}
\end{bmatrix}.
\]

The system equations show as

\[
\begin{align*}
x^{k+1} &= Ax^k + B_1u_1^k + B_2u_2^k \\
y_1^k &= C_1x^k + D_{11}u_1^k + D_{12}u_2^k \\
y_2^k &= C_2x^k + D_{21}u_1^k + D_{22}u_2^k.
\end{align*}
\]
As we invert the input-output map corresponding to \( y_1 \) and \( u_1 \), the input of this system becomes \( (y_1^k, u_2^k) \) and the output is \( (u_1^k, y_2^k) \) at time \( k \). From (B.1), as \( D_{11} \) is invertible, we have

\[
  u_1^k = -D_{11}^{-1}C_1 x^k + D_{11}^{-1} y_1^k - D_{11}^{-1} D_{112} u_2^k.
\]

The new system equations change to

\[
  x^{k+1} = (A - B_1 D_{11}^{-1} C_1) x^k + B_1 D_{11}^{-1} y_1^k + (B_2 - B_1 D_{11}^{-1} D_{12}) u_2^k \\
  y_1^k = -D_{11}^{-1} C_1 x^k + D_{11}^{-1} y_1^k - D_{11}^{-1} D_{12} u_2^k \\
  y_2^k = (C_2 - D_{21} D_{11}^{-1} C_1) x^k + D_{21} D_{11}^{-1} y_1^k + (D_{22} - D_{21} D_{11}^{-1} D_{12}) u_2^k,
\]

which correspond to state-space realization (B.2)

\[
\begin{bmatrix}
  A - B_1 D_{11}^{-1} C_1 & -\hat{D}_{11}^1 C_1 \\
  -D_{11}^{-1} D_{112} & -\hat{D}_{11}^2 \\
  (C_2 - D_{21} D_{11}^{-1} C_1) & D_{21} D_{11}^{-1}
\end{bmatrix}.
\]

To calculate the transfer function, note that

\[
  (zI - A + B_1 D_{11}^{-1} C_1)^{-1} = (zI - A)^{-1} + (zI - A)^{-1} B_1 (-D_{11} - C_1 (zI - A)^{-1} B_1)^{-1} C_1 (zI - A)^{-1}
\]

We have

\[
  \hat{H}_{11}(z) = -D_{11}^{-1} C_1 ((zI - A)^{-1} - (zI - A)^{-1} B_1 \hat{H}_{11}^{-1}(z) C_1 (zI - A)^{-1}) B_1 D_{11}^{-1} + D_{11}^{-1}
  = -D_{11}^{-1} (\hat{H}_{11}(z) - D_{11} - (\hat{H}_{11}(z) - D_{11}) \hat{H}_{11}^{-1}(z)(\hat{H}_{11}(z) - D_{11})) D_{11}^{-1} + D_{11}^{-1}
  = -D_{11}^{-1} (\hat{H}_{11}(z) - D_{11}) (I - \hat{H}_{11}^{-1}(z)(\hat{H}_{11}(z) - D_{11})) D_{11}^{-1} + D_{11}^{-1}
  = -D_{11}^{-1} (\hat{H}_{11}(z) - D_{11}) \hat{H}_{11}^{-1}(z) + D_{11}^{-1}
  = \hat{H}_{11}(z)
\]

\[
  \hat{H}_{12}(z) = -D_{11}^{-1} C_1 ((zI - A)^{-1} - (zI - A)^{-1} B_1 \hat{H}_{11}^{-1}(z) C_1 (zI - A)^{-1}) B_2 - \hat{H}_{11}^{-1}(z) D_{12}
  = -D_{11}^{-1} (\hat{H}_{12}(z) - D_{12} - (\hat{H}_{12}(z) - D_{12}) \hat{H}_{11}^{-1}(z)(\hat{H}_{12}(z) - D_{12})) - \hat{H}_{11}^{-1}(z) D_{12}
  = -D_{11}^{-1} (I - (\hat{H}_{11}(z) - D_{11}) \hat{H}_{11}^{-1}(z)(\hat{H}_{12}(z) - D_{12}) - \hat{H}_{11}^{-1}(z) D_{12}
  = -\hat{H}_{11}^{-1}(z)(\hat{H}_{12}(z) - D_{12}) - \hat{H}_{11}^{-1}(z) D_{12}
  = -\hat{H}_{11}^{-1}(z) \hat{H}_{12}(z)
\]

\[
  \hat{H}_{21}(z) = C_2 ((zI - A)^{-1} - (zI - A)^{-1} B_1 \hat{H}_{11}^{-1}(z) C_1 (zI - A)^{-1}) B_2 - \hat{H}_{11}^{-1}(z) C_2
  = (\hat{H}_{21}(z) - D_{21} - (\hat{H}_{21}(z) - D_{21}) \hat{H}_{11}^{-1}(z)(\hat{H}_{11}(z) - D_{11})) D_{11}^{-1} + D_{21} \hat{H}_{11}^{-1}(z)
  = (\hat{H}_{21}(z) - D_{21}) (I - \hat{H}_{11}^{-1}(z)(\hat{H}_{11}(z) - D_{11})) D_{11}^{-1} + D_{21} \hat{H}_{11}^{-1}(z)
  = (\hat{H}_{21}(z) - D_{21}) \hat{H}_{11}^{-1}(z) + D_{21} \hat{H}_{11}^{-1}(z)
  = \hat{H}_{21}(z) \hat{H}_{11}^{-1}(z)
\]

\[
  \hat{H}_{22}(z) = \hat{H}_{22}(z) - (\hat{H}_{21}(z) - D_{21}) \hat{H}_{11}^{-1}(z)(\hat{H}_{12}(z) - D_{12}) - D_{21} \hat{H}_{11}^{-1}(z)(\hat{H}_{12}(z) - D_{12})
  = \hat{H}_{22}(z) - \hat{H}_{21}(z) \hat{H}_{11}^{-1}(z) \hat{H}_{12}(z).
\]

Thus, we get the desired results as (4.14).

**Appendix C. Proof of proposition 6.1.**

Given an algorithm \( A \) with state-space realization \((A, B, C, D)\), the relation between the input \( u \) and output \( y \) can be expressed as

\[
  y^k = C(A)^k x^0 + \sum_{j=0}^{k-1} C(A)^{k-(j+1)} B u^j + D u^k.
\]
Relation \((C.1)\) is obtained by \((4.5)\), without the assumption that \(x^0 = 0\). The output \(y^k\) is the sum of \(C(A)^k x^0\), which is due to the initial condition \(x^0\), and \(\sum_{j=0}^{k-1} C(A)^{k-(j+1)} Bu^j + Du^k\), which is due to the inputs \(\{u^0, \ldots, u^k\}\). The linearity of \(A\) (\(A\) is treated as a linear system) allows the decomposition of two contributions and they can be studied separately:

\[
\text{(total response)} = \underbrace{\text{(zero input response)}}_{\text{set } u^k = 0 \text{ for } k \geq 0} + \underbrace{\text{(zero state response)}}_{\text{set } x^0 = 0}.
\]

Since we would like to characterize \(A\) with its input-output map, we can only focus on the zero state response, which allows us to avoid details about initialization. With the definition of impulse response,

\[
H^k = \begin{cases} 
D & k = 0 \\
C(A)^{k-1}B & k \geq 1,
\end{cases}
\]

we can express the zero state response as

\[
y^k = H^k u^0 + H^{k-1} u^1 + \cdots + H^1 u^{k-1} + H^0 u^k.
\]

Transfer function provides a compact form to represent the \(H^k\) series by taking the \(z\)-transform. The transfer function \(H(z)\) shows as follows,

\[
\hat{H}(z) = \left[ \frac{A}{C} \right] = D + \sum_{k=1}^{\infty} C(A)^{k-1}Bz^{-k} = C(zI - A)^{-1}B + D.
\]

Therefore, we know that algorithm \(A\) is uniquely characterized by its input-output map, and thus uniquely characterized by its impulse response and transfer function.

From the definition of oracle equivalence, oracle-equivalent algorithms have identical sequences of output \(y\) for each possible sequence of input \(u\) if initialized properly. Here \(y = \{y^k\}_k^\infty\) and \(u = \{u^k\}_k^\infty\). Thus, they must have identical impulse responses and consequently identical transfer functions. This completes the proof.

**Appendix D. Proof of proposition 7.1.**

**Algorithm D.1** General form of algorithm \(A\)

```plaintext
for \(k = 0, 1, 2, \ldots\) do
    \(x^k_1 = L_1(x^k_1, \ldots, x^k_m)\)
    \(x^k_2 = L_2(x^k_1, \ldots, x^k_m)\)
    \(\vdots\)
    \(x^k_i = L_i(x^k_1, \ldots, x^k_{i-1}, x^k_i, \ldots, x^k_m, u^k_{i+1})\)
    \(\vdots\)
    \(x^k_n = L_n(x^k_1, \ldots, x^k_{n-1}, x^k_n, u^k_{n+1})\)
end for
```

First, we prove that cyclic permutation implies shift equivalence. Without loss of generality, we can express algorithm \(A\) in the general form as **algorithm D.1**. Since \(A\) is an linear algorithm, \(L_1, \ldots, L_m\) are linear functions. Given an initialization \(\{x^0_1, \ldots, x^0_m\}\), \(A\) generates state sequence \(\{x^k_1, \ldots, x^k_m\}_k^0\), input sequence \(\{u^k_1, \ldots, u^k_m\}_k^0\), and output sequence \(\{y^k_1, \ldots, y^k_n\}_k^0\). The ith update equation is the first update equation that contains an oracle call, corresponding to \(u^k_i\) and \(y^k_i\). The ith update equation is the last update equation that contains an oracle call, corresponding to \(u^k_n\) and \(y^k_n\). The outputs are also linear functions of
the states. Specifically, we have

\[ y^k_1 = Y_1(x^k_1, \ldots, x^k_{i-1}, x^k_i, \ldots, x^k_m), \quad u^k_1 = \phi_1(y^k_1) \]

\[ \vdots \]

\[ y^k_n = Y_n(x^k_1, \ldots, x^k_{i-1}, x^k_i, \ldots, x^k_m), \quad u^k_n = \phi_1(y^k_n). \]

Functions \( Y_1, \ldots, Y_n \) are linear functions and \( \phi_1, \ldots, \phi_n \) denote the oracle calls. Without loss of generality, suppose permutation \( \pi = (\ell + 1, \ldots, m, 1, \ldots, \hat{\ell}) \) with \( 1 < \hat{\ell} < m \).

First case. Suppose the new order of oracle calls within one iteration is a cyclic permutation \( \pi \) of \( (n) \) (not identical to \( (n) \)). Without loss of generality, suppose \( \pi = (j + 1, \ldots, n, 1, \ldots, j) \) with \( 1 < j < n \), the \( j \)th oracle call corresponds to the \( j \)th update equation, and the \( j + 1 \)th oracle call corresponds to the \( \hat{p} \)th update equation. By definition, we have \( i \leq \hat{j} < l + 1 < \hat{\rho} \leq \hat{i} \). At the first time step \( k = 1 \), the first input is \( u^1_1 \) and the first output is \( y^1_1 \), and the \( j + 1 \)th input and output are \( u^{j+1}_{j+1} \) and \( y^{j+1}_{j+1} \). We have

\[ y^1_1 = Y_1(x^1_1, \ldots, x^1_{i-1}, x^1_i, \ldots, x^1_m) \]

\[ y^{j+1}_{j+1} = Y_j(x^j_1, \ldots, x^j_{\hat{\rho}-1}, x^j_{\hat{\rho}}, \ldots, x^j_m). \]

Here without loss of generality, suppose the \( \hat{l} + 1 \)th update equation does not contain an oracle call. In other words, \( \hat{j} < \hat{l} + 1 < \hat{\rho} \). By definition, \( B \) calls the update equations in the order \( \hat{\pi} \). At the first time step, the \( \hat{l} + 1 \)th update equation is first called. If \( B \) is suitably initialized with states \( \{x^1_1, \ldots, x^1_{\hat{l}}, x^0_{\hat{l}+1}, \ldots, x^0_m\} \), it will generate state sequence \( (x^{k+1}_{\hat{l}+1}, \ldots, x^{k+1}_m, x^{k+1}, \ldots, x^{k+1})_{k \geq 0} \), input sequence \( (u^k_{\hat{l}+1}, \ldots, u^k_m, u^{k+1}_1, \ldots, u^{k+1}_{j+1})_{k \geq 1} \), and output sequence \( (y^k_{\hat{l}+1}, \ldots, y^k_n, y^{k+1}_1, \ldots, y^{k+1}_{j+1})_{k \geq 1} \). The input and output sequences of \( A \) and \( B \) match up to prefixes \( (u^1_1, \ldots, u^1_{\hat{l}}) \) and \( (y^1_1, \ldots, y^1_{\hat{j}}) \) respectively. Therefore, \( A \) and \( B \) are shift-equivalent.

Second case. Suppose the order of oracle calls within one iteration remain unchanged (identical to \( (n) \)). By definition, we have \( 1 < \hat{l} + 1 \leq i \). We have

\[ x^1_{\hat{l}+1} = L_{\hat{l}+1}(x^1_1, \ldots, x^1_{i-1}, x^1_{i+1}, \ldots, x^1_m) \]

\[ y^1_1 = Y_1(x^1_1, \ldots, x^1_{i-1}, x^1_i, \ldots, x^1_m). \]

Here without loss of generality, suppose the \( \hat{l} + 1 \)th update equation does not contain an oracle call. In other words, \( \hat{l} + 1 < i \). By definition, \( B \) calls the update equations in the order \( \hat{\pi} \). At the first time step, the \( \hat{l} + 1 \)th update equation is first called. If \( B \) is suitably initialized with states \( \{x^1_1, \ldots, x^1_{\hat{l}}, x^0_{\hat{l}+1}, \ldots, x^0_m\} \), it will generate state sequence \( (x^{k+1}_{\hat{l}+1}, \ldots, x^{k+1}_m, x^{k+1}, \ldots, x^{k+1})_{k \geq 0} \), input sequence \( (u^k_{\hat{l}+1}, \ldots, u^k_m, u^{k+1}_1, \ldots, u^{k+1}_{j+1})_{k \geq 1} \), and output sequence \( (y^k_{\hat{l}+1}, \ldots, y^k_n, y^{k+1}_1, \ldots, y^{k+1}_{j+1})_{k \geq 1} \). The input and output sequences remain unchanged. Therefore, \( A \) and \( B \) are oracle-equivalent. Meanwhile, since oracle equivalence can be regarded as a special case of shift equivalence, \( A \) and \( B \) are also shift-equivalent.

Next, we prove that shift equivalence implies cyclic permutation. Suppose algorithms \( A \) and \( B \) are shift-equivalent. If they are also oracle-equivalent, then they can be written using the same set of update equations, which is trivially related by a cyclic permutation (where the permutation is the identity). Now suppose they are not oracle-equivalent. Let \( (u^k_1, \ldots, u^k_m)_{k \geq 0} \) and \( (\hat{u}^k_1, \ldots, \hat{u}^k_m)_{k \geq 0} \) be the input sequences for \( A \) and \( B \). The input sequences match up to a non-empty prefix. Without loss of generality, suppose the length of this prefix is \( q \): that is, if we remove a prefix of length \( q \) from the input sequence of \( A \), then \( A \) and \( B \) have the same input sequence. Recall we only need to consider the case \( q < m \). If \( q > m \), it is equivalent to consider \( q = q \mod m \). Comparing the input sequences of \( A \) and \( B \), and using the prefix length \( q \), we can write \( (u^k_{q+1}, \ldots, u^k_m)_{k \geq 0} = (\hat{u}^k_{q+1}, \ldots, \hat{u}^k_m)_{k \geq 0} \) for \( k \geq 1 \). The output sequences of \( A \) and \( B \) have the same relation. Therefore, \( B \) and this shifted version of \( A \) are oracle equivalent, and so we can write \( B \) and this shifted version of \( A \) using the same set of update equations. To undo the shift of \( A \), we simply move the first \( q \) update equations to the end of the algorithm.

Appendix E. Proof of proposition 7.3.
The state-space realization of $\mathcal{A}$ corresponds to the state update equations

\begin{align}
x^{k+1} &= Ax^k + B_1 u_1^k + B_2 u_2^k \\
\bar{y}_1^k &= C_1 x^k + D_{11} \bar{u}_1^k + D_{12} \bar{u}_2^k \\
\bar{y}_2^k &= C_2 x^k + D_{21} \bar{u}_1^k + D_{22} \bar{u}_2^k.
\end{align}

(E.1)

Sufficiency. We will derive the state-space realization of $P_{x,\mathcal{A}}$:

\[
\begin{bmatrix}
A & B_1 & 0 & B_2 \\
0 & 0 & I & 0 \\
C_1 A - C_1 B_1 & C_1 - D_{11} & C_1 B_2 & - C_1 B_2 \\
C_2 & D_{21} & 0 & D_{22}
\end{bmatrix}
\]

To verify this realization is correct, we can write the system equations of this state-space realization as

\begin{align}
x^{k+1} &= Ax^k + B_1 \bar{u}_1^k + B_2 \bar{u}_2^k \\
\bar{u}_1^{k+1} &= \bar{u}_1^k \\
\bar{y}_1^{k+1} &= C_1 Ax^k + C_1 B_1 \bar{u}_1^k + D_{11} \bar{u}_1^{k+1} + C_1 B_2 \bar{u}_2^k \\
\bar{y}_2^k &= C_2 x^k + D_{21} \bar{u}_1^k + D_{22} \bar{u}_2^k.
\end{align}

(E.2)

Note that equations (E.2) are the results of equations (E.1) after applying permutation $\pi$. As we perform cyclic permutation $\pi$, within each iteration, the update order of the oracles is shifted as $(j+1, \ldots, n, 1, \ldots, j)$, indicating oracles $(j+1, \ldots, n)$ are updated before $(1, \ldots, j)$. Further, the input and output sequences within one iteration at time step $k$ become $(\bar{u}_2^k, \bar{u}_1^{k+1})$ and $(\bar{y}_2^k, \bar{y}_1^{k+1})$. From the state-space realization, we may compute the transfer function as

\[
\hat{H}_B(z) = \begin{bmatrix}
C_1 (zI - A)^{-1} B_1 + D_{11} \\
C_2 (zI - A)^{-1} B_1 / z + D_{21} / z \\
C_2 (zI - A)^{-1} B_2 + D_{22}
\end{bmatrix} = \begin{bmatrix}
\hat{H}_{11}(z) \\
\hat{H}_{21}(z) / z \\
\hat{H}_{22}(z)
\end{bmatrix}.
\]

To arrive at (E.3), we have used the fact that $D_{12} = 0$ by assumption, and

\[
(zI - \begin{bmatrix}
A & B_1 \\
0 & 0
\end{bmatrix})^{-1} = \begin{bmatrix}
(zI - A)^{-1} & \frac{1}{z} (zI - A)^{-1} B_1 \\
0 & \frac{1}{z} I
\end{bmatrix}.
\]

Necessity is provided by proposition 6.1. Equivalent algorithms must have identical transfer functions. Thus, if we find an algorithm and its transfer function is the same as (7.2), it must be equivalent to $\mathcal{B}$.

**Appendix F. Discussions on permutation and its generalization.** To take a revisit of proposition 7.3, it can be found that as algorithm $\mathcal{A}$ is permuted to make the order of oracle calls within one iteration as $(j+1, \ldots, n, 1, \ldots, j)$ from $(1, \ldots, n)$, the resulting transfer function is exactly the same as adding a one-step time delay to channels (oracles) $(1, \ldots, j)$ according to results in control theory. Another interpretation of adding a one-step time delay comes from the system equations (E.2). We can see that the input and output corresponding to channels (oracles) $(1, \ldots, j)$ are the input and output for the next time step $\bar{u}_1^{k+1}$ and $\bar{y}_1^{k+1}$, however, the input and output of channels (oracles) $(j+1, \ldots, n)$ are still the ones for the current time step $\bar{u}_2^k$ and $\bar{y}_2^k$. Intrinsically, after cyclic permutation, the intrinsic update order of oracles does not change, but a one-step time delay is added to the oracles that we would like to update latterly.

Using the idea of time delay, we can generalize algorithm permutation as adding any step of time delay to any channel (oracle) of an algorithm. Suppose we add time delay to oracle $i$ of algorithm $\mathcal{A}$ by $d_i$ for any $i \in (n)$, where $d_i$ can be any integer, the resulting algorithm $\mathcal{B}$ has transfer function $\hat{H}_B(z)$ as

\[
\hat{H}_B(z) = \begin{bmatrix}
H_1^d \\
H_2^d \\
\vdots \\
H_n^d
\end{bmatrix} \hat{H}_A(z) \begin{bmatrix}
H_1^d \\
H_2^d \\
\vdots \\
H_n^d
\end{bmatrix}^{-1},
\]

(F.1)
where $\hat{H}_A(z)$ is the transfer function of $A$.

To be more specific, suppose we add time delay $d_i$ to oracle $i$ for algorithm $A$, $h^{k}_{ij}(z)$ with $1 \leq k \leq n$ and $1 \leq l \leq n$ denotes the entry of $H_A(z)$. The transfer function of the resulting algorithm $B$ can be expressed entrywise as

$$
(F.2) \quad h^{k}_{ij}(z) = \begin{cases} 
  h^{i}_{ij}(z) & k = i \ l = i \\
  h^{i}_{ij}(z)z^{-d_i} & k = i \ l \neq i \\
  h^{k}_{ij}(z) & k \neq i \ l = i \\
  h^{k}_{ij}(z) & k \neq i \ l \neq i
\end{cases}
$$

In this way, we know that proposition 7.3 is a special case of (F.1) with $d_1 = \cdots = d_j = 1$.

However, there are restrictions so that we cannot add any arbitrary step of time delay to any oracle. From subsection 4.3, transfer functions are rational (matrix) functions with respect to $z$. Further, the rational functions must be proper in order to make the transfer function realizable. From (F.2), as we add time delay $d_i$ to oracle $i$ for $A$, the off-diagonal entries in the $i$th row of $\hat{H}_A(z)$ are multiplied by $z^{d_i}$ and the off-diagonal entries in the $i$th column of $\hat{H}_A(z)$ are multiplied by $z^{-d_i}$ while the $i$th diagonal entry remains unchanged.

From the perspective of relative degrees, as relative degree is the difference between the degree of denominator and the degree of numerator, the relative degrees of the off-diagonal entries in the $i$th row are decreased by $d_i$ but the relative degrees of the off-diagonal entries in the $i$th column are increased by $d_i$. Suppose the smallest relative degree among the off-diagonal entries in the $i$th row is $r_i$, then $d_i$ must satisfy $d_i \leq r_i$ to maintain properness of the resulting off-diagonal entries in the $i$th row. Similarly, suppose the smallest relative degree among the off-diagonal entries of the $i$th column is $c_i$, then $d_i$ must satisfy $-d_i \leq c_i$ to maintain properness of the resulting off-diagonal entries in the $i$th column. In other words, we can add time delay $d_i$ to oracle $i$ only if $-c_i \leq d_i \leq r_i$. Otherwise, at least one off-diagonal entry in the $i$th row or the $i$th column is no longer proper, leading to an invalid transfer function.

For any algorithm with state-space realization $(A,B,C,D)$, the transfer function is calculated by $C(zI-A)^{-1}B+D$. Term $C(zI-A)^{-1}B$ is a strictly proper (matrix) function, where strictly proper means that the degree of $z$ in the numerator polynomial is strictly less than the degree of $z$ in the denominator polynomial. Thus, for any nonzero entry of $D$, the corresponding entry in the transfer function has relative degree zero. Take a revisit of cyclic permutation, for any causal algorithm, the entries above diagonal of the $D$ matrix must be zero, especially after necessary reordering. Thus, the entries above diagonal in the transfer function have strictly positive relative degrees. This implies that any cyclic permutation of an algorithm always exists. Note that before performing cyclic permutation, we are required to reorder the state-space realization if needed.

Reconsider algorithms 7.5 and 7.6, in (7.5) and (7.6), comparing $\hat{H}_{10}(z)$ to $\hat{H}_{11}(z)$, we add a one-step time delay to the first channel. Term $\frac{1}{z}$ in $\hat{H}_{10}(z)$ is multiplied by $z$ and term $\frac{z^{-1}}{z}$ is multiplied by $z^{-1}$. Further, the off-diagonal entry in the first row of $\hat{H}_{10}(z)$ has relative degree 1 and the off-diagonal entry in the first column of $\hat{H}_{10}(z)$ has relative degree 0. Thus, we can only add time delay $d_i = 1$ to the first oracle of algorithm 7.5, as $0 \leq d_i \leq 1$ to maintain properness.

**Appendix G. Proof of proposition 7.4.**

Partition the oracle calls of algorithm $A : \mathcal{X} \rightarrow \mathcal{X}$ into two (nonlinear) oracles $\phi_1$ and $\phi_2$. Formally, write the update equations as

$$
(G.1) \quad \begin{align*}
x^* &= Ax^* + B_1 \bar{u}_1^* + B_2 \bar{u}_2^* \\
\bar{y}_1^* &= C_1 x^* + D_{11} \bar{u}_1^* + D_{12} \bar{u}_2^* \\
\bar{y}_2^* &= C_2 x^* + D_{21} \bar{u}_1^* + D_{22} \bar{u}_2^* \\
u_1^* &= \phi_1(\bar{y}_1^*) \\
u_2^* &= \phi_2(\bar{y}_2^*).
\end{align*}
$$

Here the cyclic permutation $\pi$ swaps the first and second set of oracle calls. Then the cyclic permutation $P_\pi A$ converges to fixed point $(\bar{y}_2^*, \bar{y}_1^*, \bar{u}_2^*, \bar{u}_1^*, x^*)$. To verify this, since $D_{12} = 0$, plugging in the fixed point
conditions (G.1) to the system equations of the shifted algorithm (E.2), we have
\[ x^* = Ax^* + B_1\tilde{u}_1^* + B_2\tilde{u}_2^* \]
\[ \tilde{u}_1^* = \tilde{u}_1^* \]
\[ \tilde{y}_1^* = C_1Ax^* + C_1B_1\tilde{u}_1^* + D_{11}\tilde{u}_1^* + C_1B_2\tilde{u}_2^* = C_1x^* + D_{11}\tilde{u}_1^* \]
\[ \tilde{y}_2^* = C_2x^* + D_{21}\tilde{u}_1^* + D_{12}\tilde{u}_2^* \]
\[ u_1^* = \phi_1(y_1^*) \]
\[ u_2^* = \phi_2(y_2^*) . \]

This completes the proof.

**Appendix H. Proof of shift-equivalence of DR and ADMM continued.** Suppose the oracles for both DR (algorithm 7.5) and ADMM (algorithm 7.6) are subgradients of \( f \) and \( g \). Oracles prox and argmin can be expanded as inclusions involving subgradients. The update equations of DR and ADMM can be rewritten into formations of algorithms H.1 and H.2 respectively. Note that the update equations involving subgradients are inclusions.

**Algorithm H.1 DR**

```
for k = 0, 1, 2, ..., do
  \[ x_{1}^{k+1} = x_{3}^{k} - t\partial f(x_{1}^{k+1}) \]
  \[ x_{2}^{k+1} = 2x_{3}^{k+1} - x_{3}^{k} - tL_{1}\partial g(L_{2}x_{2}^{k+1}) \]
end for
```

**Algorithm H.2 ADMM**

```
for k = 0, 1, 2, ..., do
  \[ \xi_{1}^{k+1} \in L\xi_{1}^{k} - L\xi_{1}^{k} - \frac{1}{\rho}L_{1}\partial g(L_{2}\xi_{1}^{k}) \]
  \[ \xi_{2}^{k+1} \in L^{-1}\xi_{1}^{k+1} + \xi_{2}^{k} - \frac{1}{\rho}\partial f(\xi_{2}^{k+1}) \]
  \[ \xi_{3}^{k+1} = \xi_{3}^{k} + L^{-1}\xi_{1}^{k+1} - \xi_{2}^{k+1} \]
end for
```

We still assume \( \rho = 1/t \) in ADMM. The transfer functions are computed as \( \hat{H}_{18}(z) \) and \( \hat{H}_{19}(z) \) respectively. Note that \( \hat{H}_{19}(z) \) is not written in the causal order.

\[
\hat{H}_{18}(z) = \begin{bmatrix}
0 & 0 & I & -tI & 0 \\
0 & 0 & I & -2tI & -tL \\
0 & 0 & I & -tI & -tL \\
0 & 0 & I & -tI & 0 \\
0 & L & -L & 0 & -tLL
\end{bmatrix} = \begin{bmatrix}
\frac{-iz}{1-z^{-1}}I & \frac{iz}{1-z^{-1}}L \\
\frac{-iz}{1-z^{-1}}L & \frac{-iz}{1-z^{-1}}L
\end{bmatrix}
\]

\[
\hat{H}_{19}(z) = \begin{bmatrix}
0 & L & -L & 0 & -tL \\
0 & I & 0 & -tL & -tL \\
0 & 0 & 0 & tI & 0 \\
0 & I & 0 & -tL & -tL \\
0 & L & -L & 0 & -tL
\end{bmatrix} = \begin{bmatrix}
\frac{-iz}{1-z^{-1}}I & \frac{iz}{1-z^{-1}}L \\
\frac{-iz}{1-z^{-1}}L & \frac{-iz}{1-z^{-1}}L
\end{bmatrix}
\]

From propositions 7.1 and 7.3, we know that they are still shift-equivalent.

**Appendix I. Proof of proposition 8.1.**

**Sufficiency.** The update equations of \( B \) can be written as

\[
x_1^k = Ax_1^k + Bu_1^k \\
y_1^k = Cx_1^k + Du_1^k \\
x_{B}^{k+1} = Ax_{B}^{k} + Bu_{1}^{k} \\
y_{B}^{k} = Cx_{B}^{k} + Du_{1}^{k} \\
y_{B}^{k} = Cx_{B}^{k} + Du_{1}^{k} + Du_{2}^{k}.
\]

where \( x_{B}^{k} \) is an intermediate state. Eliminating the intermediate state \( x_{B}^{k} \), we arrive at the new update equations:

\[
x_{B}^{k+1} = A^2x_{B}^{k} + ABu_{1}^{k} + Bu_{2}^{k} \\
y_{B}^{k} = Cx_{B}^{k} + Du_{1}^{k} \\
y_{B}^{k} = Cx_{B}^{k} + Du_{1}^{k} + Du_{2}^{k}.
\]
The corresponding state-space realization has transfer function
\[
\begin{bmatrix}
A^2 & AB & B \\
C & D & 0 \\
CA & CB & D
\end{bmatrix} =
\begin{bmatrix}
C(zI - A^2)^{-1}AB + D & C(zI - A^2)^{-1}B \\
CA(zI - A^2)^{-1}AB + CB & CA(zI - A^2)^{-1}B + D
\end{bmatrix}.
\]

Necessity is provided by proposition 6.1 since the transfer function uniquely characterizes an equivalence class of algorithms.

Appendix J. Proof of proposition 8.3. Suppose the oracles of algorithm \(A : \mathcal{X} \to \mathcal{X}\) can be represented as \(\phi : \mathcal{X} \to \mathcal{X}\). Since \(A\) converges to fixed point \((y^*, u^*, x^*)\), it satisfies
\[
\begin{align*}
x^* &= Ax^* + Bu^* \\
y^* &= Cx^* + Du^* \\
u^* &= \phi(y^*).
\end{align*}
\]

Therefore, we have
\[
\begin{align*}
x^* &= A^nx^* + Bu^* \\
&= A(Ax^* + Bu^*) + Bu^* \\
&= A^2x^* + ABu^* + Bu^* \\
&= \ldots \\
&= A^{n-1}x^* + A^{n-2}Bu^* + \cdots + ABu^* + Bu^* \\
&= A^nx^* + A^{n-1}Bu^* + \cdots + ABu^* + Bu^* \\
y^* &= Cx^* + Du^* \\
&= CAx^* + CBu^* + Du^* \\
&= \ldots \\
&= CA^{n-1}x^* + CA^{n-2}Bu^* + \cdots + C Bu^* + Du^*.
\end{align*}
\]

With (8.2), we have
\[
\begin{align*}
x^* &= A^nx^* + A^{n-1}Bu^* + \cdots + ABu^* + Bu^* \\
y^* &= Cx^* + Du^* \\
y^* &= CA^{n-1}x^* + C Bu^* + Du^* \\
&= \ldots \\
y^* &= CA^{n-1}x^* + CA^{n-2}Bu^* + \cdots + C Bu^* + Du^*,
\end{align*}
\]

which indicates that \(A^n\) converges to fixed point \((y', u', x')\) with \(y' = y^* \otimes \mathbb{1}^n\) and \(u' = u^* \otimes \mathbb{1}^n\).

Appendix K. Proof of proposition 9.3. Without loss of generality, let the permutation matrix equal to the identity as proposition 9.1. To simplify the notations, let
\[
\begin{bmatrix}
A & B & B[[n], \bar{k}] \\
C & \bar{D} & D[[n], \bar{k}] \\
\bar{C} & \bar{D} & D[[n], \bar{k}]
\end{bmatrix} =
\begin{bmatrix}
A & B_1 & B_2 \\
\bar{C}_1 & \bar{D}_1 & \bar{D}_2 \\
C_2 & D_1 & D_2
\end{bmatrix},
\]

\[
\begin{bmatrix}
\bar{H}[\bar{k}](z) & \bar{H}[\bar{k}, \bar{k}](z) \\
\bar{H}[\bar{k}, \bar{k}](z) & \bar{H}[\bar{k}](z)
\end{bmatrix} =
\begin{bmatrix}
\bar{H}_{11}(z) & \bar{H}_{12}(z) \\
\bar{H}_{21}(z) & \bar{H}_{22}(z)
\end{bmatrix} =
\begin{bmatrix}
C_1(zI - A)^{-1}B_1 + D_1 & C_1(zI - A)^{-1}B_2 + D_2 \\
C_2(zI - A)^{-1}B_1 + D_2 & C_2(zI - A)^{-1}B_2 + D_2
\end{bmatrix}.
\]

In this way, \((y[\bar{k}], y[\bar{k}]^*, u[\bar{k}], u[\bar{k}]^*, x^*)\) can be written as \((y_1^*, y_2^*, u_1^*, u_2^*, x^*)\), and \((u[\bar{k}], y[\bar{k}]^*, y[\bar{k}], u[\bar{k}]^*, x^*)\) can be written as \((u_1^*, y_2^*, y_1^*, u_2^*, x^*)\).
Partition the oracle calls of algorithm $\mathcal{A} : \mathcal{X} \to \mathcal{X}$ into two nonlinear oracles $\phi_1$ and $\phi_2$. Oracle $\phi_1$ corresponds to the oracle calls in set $\kappa$, and $\phi_2$ corresponds to the remaining oracle calls. Since $\mathcal{A}$ converges to fixed point $(y^*_1, y^*_2, u^*_1, u^*_2, x^*)$, it satisfies

$$
x^* = Ax^* + B_1u^*_1 + B_2u^*_2
$$

$$
y^*_1 = C_1x^* + D_{11}u^*_1 + D_{12}u^*_2
$$

$$
y^*_2 = C_2x^* + D_{21}u^*_1 + D_{22}u^*_2
$$

$$
u^*_1 = \phi_1(y^*_1)
$$

$$
u^*_2 = \phi_2(y^*_2).
$$

The state-space realization of $\mathcal{C}_\kappa \mathcal{A}$ is the same as (B.2). Note that $D_{11}$ is invertible, we have

$$
x^* = Ax^* + B_2u^*_2 + B_1u^*_1
$$

$$
= Ax^* + B_2u^*_2 + B_1(-D_{11}^{-1}C_1x^* + D_{11}^{-1}y^*_1 - D_{11}^{-1}D_{12}u^*_2)
$$

$$
= (A - B_1D_{11}^{-1}C_1)x^* + B_1D_{11}^{-1}y^*_1 + (B_2 - B_1D_{11}^{-1}D_{12})u^*_2
$$

$$
u^*_1 = -D_{11}^{-1}C_1x^* + D_{11}^{-1}y^*_1 - D_{11}^{-1}D_{12}u^*_2
$$

$$
y^*_2 = C_2x^* + D_{22}u^*_2 + D_{21}u^*_1
$$

$$
= C_2x^* + D_{22}u^*_2 + D_{21}(D_{11}^{-1}y^*_1 - D_{11}^{-1}C_1x^* - D_{11}^{-1}D_{12}u^*_2)
$$

$$
= (C_2 - D_2D_{11}^{-1}C_1)x^* + D_{21}D_{11}^{-1}y^*_1 + (D_{22} - D_2D_{11}^{-1}D_{12})u^*_2
$$

$$
u^*_2 = \phi_2(y^*_2).
$$

Oracle $\phi^{-1}_1$ is the inverse oracle of oracle $\phi_1$. Therefore, we get the desired results that algorithm $\mathcal{C}_\kappa \mathcal{A}$ converges to fixed point $(u^*_1, y^*_2, y^*_1, u^*_2, x^*)$.

**Appendix I. Commutativity between conjugation and cyclic permutation.**

**Proposition I.1.** Conjugation and cyclic permutation commute.

**Proof.** Given an algorithm $\mathcal{A}$ with transfer function $\tilde{H}(z)$. Suppose $\kappa$ is a subset of the oracles of $\mathcal{A}$, $D_\kappa$ is invertible, and $\pi = (m + 1, \ldots, n, 1, \ldots, m)$ is an arbitrary cyclic permutation of the oracles of $\mathcal{A}$. We will show that the transfer functions of $\mathcal{C}_\pi P_\pi \mathcal{A}$ and $P_\pi \mathcal{C}_\kappa \mathcal{A}$ are identical.

Suppose $\tilde{H}^*(z)$ is the transfer function of $P_\pi \mathcal{A}$, the results in **proposition 7.3** can be written as

$$
\tilde{H}^*(z) = Q\tilde{H}(z)Q^{-1}.
$$

Here $Q$ is a diagonal matrix where the first $m$ diagonal entries are all $z$ and the rest of the diagonal entries are all ones. We will use the same settings and notations as **proposition 9.1** to express changes in transfer function of conjugation $\mathcal{C}_\kappa$. Without loss of generality, the transfer function $\tilde{H}^*(z)$ of $\mathcal{C}_\kappa \mathcal{A}$ satisfies

$$
\tilde{H}^*(z) = \begin{bmatrix}
\tilde{H}^{-1}_{11}(z) & -\tilde{H}^{-1}_{12}(z)
\tilde{H}^{-1}_{21}(z) & \tilde{H}^{-1}_{22}(z)
\end{bmatrix}.
$$

Thus we can partition matrix $Q$ as $\text{diag}(Q_1, Q_2)$, where $Q_1$ corresponds to the oracles in $\kappa$ and $Q_2$ corresponds to the rest part of oracles. Consequently, $Q^{-1}$ can be written as $\text{diag}(Q_1^{-1}, Q_2^{-1})$.

From (L.1) and (L.2), we have

$$
\tilde{H}(z) \overset{\mathcal{C}_\kappa}{\longrightarrow} \begin{bmatrix}
\tilde{H}^{-1}_{11}(z) & -\tilde{H}^{-1}_{12}(z)
\tilde{H}^{-1}_{21}(z) & \tilde{H}^{-1}_{22}(z)
\end{bmatrix}
$$

$$
\overset{P_\pi}{\longrightarrow} \begin{bmatrix}
Q_1\tilde{H}^{-1}_{11}(z)Q_1^{-1} & -Q_1\tilde{H}^{-1}_{12}(z)Q_2^{-1}
Q_2\tilde{H}^{-1}_{21}(z)Q_1^{-1} & Q_2\tilde{H}^{-1}_{22}(z)Q_2^{-1}
\end{bmatrix},
$$

$$
\overset{\mathcal{C}_\pi}{\longrightarrow} \begin{bmatrix}
\tilde{H}^{11}_{11}(z)Q_1^{-1} & -\tilde{H}^{11}_{12}(z)Q_2^{-1}
\tilde{H}^{11}_{21}(z)Q_1^{-1} & \tilde{H}^{11}_{22}(z)Q_2^{-1}
\end{bmatrix}.
$$
We get the desired results to show $C_n$ and $P_n$ commute. Therefore, conjugation and cyclic permutation commute.

**Appendix M. Proof of (A.4) and (A.5).** For each $i \in \{1, \ldots, n\}$ we have

\[
z_i = \arg\min_x \left\{ \lambda_i f_i(x) + \frac{1}{2} \begin{bmatrix} x \\ y_i \end{bmatrix}^T \begin{bmatrix} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \end{bmatrix} \begin{bmatrix} x \\ y_i \end{bmatrix} \right\}.
\]

Besides, $Q_{11}^i$ is invertible for any $i \in \{1, \ldots, n\}$. Since $f_i$ is a convex function, the argmin oracle can be written as $z_i \in -Q_{11}^{-1} \lambda \partial f_i(z_i) - Q_{11}^{-1} Q_{12} y_i$ by treating $\partial f_i$ as the oracle. Written into matrix form, we have

\[(M.1) \quad \tilde{u}_i = -Q_1^{-1} \lambda \tilde{u}_1 - Q_1^{-1} Q_2 y_1,
\]

where $\tilde{u}_1 = [\partial f_1(z_1), \ldots, \partial f_n(z_n)]^T$. Combine (M.1) with the state-space realization (A.2), we get the desired results for (A.4). The corresponding system equations show as

\[
x^{k+1} = (A - B_1(I + M_1 D_{11})^{-1} M_1 C_1)x^k - B_1(I + M_1 D_{11})^{-1} M_1 D_{12} \tilde{u}_1^k + (B_2 - B_1(I + M_1 D_{11})^{-1} M_1 D_{12}) \tilde{u}_2^k \]

\[
\tilde{u}_1^k = -(I + M_1 D_{11})^{-1} M_1 C_1 x^k - (I + M_1 D_{11})^{-1} M_1 D_{12} \tilde{u}_2^k - (I + M_1 D_{11})^{-1} M_1 D_{12} \tilde{u}_2^k \]

\[
\tilde{y}_k = (C_2 - D_{21}(I + M_1 D_{11})^{-1} M_1 C_1)x^k - D_{21}(I + M_1 D_{11})^{-1} M_1 \tilde{u}_1^k + (D_{22} - D_{21}(I + M_1 D_{11})^{-1} M_1 D_{12}) \tilde{u}_2^k.
\]

To calculate the transfer function, note that

\[
(zI - A + B_1(I + M_1 D_{11})^{-1} M_1 C_1)^{-1} = (zI - A)^{-1} - (zI - A)^{-1} B_1(I + M_1 \hat{H}_{11}(z))^{-1} M_1 C_1 (zI - A)^{-1} - (zI - A)^{-1} B_1(I + M_1 \hat{H}_{11}(z))^{-1} M_1 C_1 (zI - A)^{-1}.
\]

We have

\[
\hat{H}_{11}(z) = (I + M_1 D_{11})^{-1} M_1 C_1 (zI - A + B_1(I + M_1 D_{11})^{-1} M_1 C_1)^{-1} B_1(I + M_1 D_{11})^{-1} M_2 - (I + M_1 D_{11})^{-1} M_2
\]

\[
= (I + M_1 D_{11})^{-1} (M_1 \tilde{H}_{11}(z) - M_1 D_{11})(I - (I + M_1 \tilde{H}_{11}(z))^{-1} (M_1 \tilde{H}_{11}(z) - M_1 D_{11}))(I + M_1 D_{11})^{-1} M_2
\]

\[
= - (I + M_1 D_{11})^{-1} M_2
\]

\[
\hat{H}_{12}(z) = -(I + M_1 D_{11})^{-1} M_1 C_1 (zI - A + B_1(I + M_1 D_{11})^{-1} M_1 C_1)^{-1} B_2 - (I + M_1 \tilde{H}_{11}(z))^{-1} M_1 D_{12}
\]

\[
= -(I + M_1 D_{11})^{-1} (I - (M_1 \tilde{H}_{11}(z) - M_1 D_{11})(I + M_1 \tilde{H}_{11}(z))^{-1})(M_1 \tilde{H}_{11}(z) - M_1 D_{12})
\]

\[
= - (I + M_1 \tilde{H}_{11}(z))^{-1} M_1 D_{12}
\]

\[
\hat{H}_{21}(z) = -C_2(zI - A + B_1(I + M_1 D_{11})^{-1} M_1 C_1)^{-1} B_1(I + M_1 D_{11})^{-1} M_2 - D_{21}(I + M_1 \tilde{H}_{11}(z))^{-1} M_2
\]

\[
= -(H_{21}(z) - D_{21})(I - (I + M_1 \tilde{H}_{11}(z))^{-1}(M_1 \tilde{H}_{11}(z) - M_1 D_{11}))(I + M_1 D_{11})^{-1} M_2
\]

\[
= -D_{21}(I + M_1 \tilde{H}_{11}(z))^{-1} M_2
\]

\[
= -(H_{21}(z) - D_{21})(I + M_1 \tilde{H}_{11}(z))^{-1} M_2
\]

\[
= -(H_{21}(z) - D_{21})(I + M_1 \tilde{H}_{11}(z))^{-1} M_2
\]

\[
= -(H_{21}(z) - D_{21})(I + M_1 \tilde{H}_{11}(z))^{-1} M_2
\]

\[
\hat{H}_{22}(z) = \hat{H}_{22}(z) - (\hat{H}_{21}(z) - D_{21})(I + M_1 \tilde{H}_{11}(z))^{-1} M_1(\hat{H}_{12}(z) - D_{12}) - D_{21}(I + M_1 \tilde{H}_{11}(z))^{-1} M_1(\hat{H}_{12}(z) - D_{12})
\]

\[
= \hat{H}_{22}(z) - \hat{H}_{21}(z)(I + M_1 \tilde{H}_{11}(z))^{-1} M_1 D_{12} - D_{21}(I + M_1 \tilde{H}_{11}(z))^{-1} M_1 D_{12}
\]

Thus, we get the desired results as (A.5).