WILLUMP: A STATISTICALLY-AWARE END-TO-END OPTIMIZER FOR
MACHINE LEARNING INFERENCE

Peter Kraft 1 Daniel Kang 1 Deepak Narayanan 1 Shoumik Palkar 1 Matei Zaharia 1 Peter Bailis 1

ABSTRACT

Systems for performing ML inference are widely deployed today. However, they typically use techniques designed for conventional data serving workloads, missing critical opportunities to leverage the statistical nature of ML inference. In this paper, we present WILLUMP, an optimizer for ML inference that introduces two statistically-motivated optimizations targeting ML applications whose performance bottleneck is feature computation. First, WILLUMP automatically cascades feature computation. WILLUMP classifies most data inputs using only high-value, low-cost features selected by a dataflow analysis algorithm and cost model, improving performance by up to 5× without statistically significant accuracy loss. Second, WILLUMP accurately approximates ML top-K queries, discarding low-scoring inputs with an automatically constructed approximate model then ranking the remainder with a more powerful model, improving performance by up to 10× with minimal accuracy loss. Both optimizations automatically tune their own parameters to maximize performance while meeting a target accuracy level. WILLUMP combines these novel optimizations with powerful compiler optimizations to automatically generate fast inference code for ML applications. We show that WILLUMP improves the end-to-end performance of real-world ML inference pipelines curated from major data science competitions by up to 16× without statistically significant loss of accuracy.

1 INTRODUCTION

The importance of machine learning in modern data centers has sparked interest in model serving systems, which perform ML inference and serve predictions to end-user applications (Crankshaw et al., 2017; Wang et al., 2018). Model serving systems typically approach ML inference as an extension of conventional data serving workloads, missing critical opportunities to exploit the statistical nature of ML inference. Most modern model serving systems, such as Clipper (Crankshaw et al., 2017), Amazon Sagemaker, and Microsoft AzureML, treat ML inference as a black box and implement generic systems optimizations such as caching and adaptive batching. Some systems, such as Pretzel (Lee et al., 2018), also apply traditional compiler optimizations.

These optimizations are useful in ML inference, just as they are for web applications or database queries. However, systems for optimizing ML inference can leverage two key properties of ML not found in general data serving:

- **ML models can often be approximated efficiently on many inputs:** For example, the computer vision community has long used “model cascades” where a low-cost model classifies “easy” inputs and a higher-cost model classifies inputs where the first is uncertain, resulting in much faster inference with negligible change in accuracy (Viola & Jones, 2001; Wang et al., 2017). By contrast, existing multi-purpose model serving systems handle all data inputs the same way.
- **ML models are often used in higher-level application contexts, such as top-K queries.** However, existing model serving systems are unaware of these query modalities. As we show, tailoring inference to the query (for WILLUMP, top-K queries) can improve performance.

To leverage these opportunities for optimization, we present WILLUMP, a statistically-aware end-to-end optimizer for ML inference. WILLUMP targets a common class of ML inference applications: those whose performance bottleneck is feature computation. In these applications, a pipeline of transformations converts raw input data into numerical features used by an ML model to make predictions. These applications are common, especially when performing ML inference over tabular data. For example, Pretzel’s study of ML inference at Microsoft found that feature computation accounted for as much as 99.7% of the runtime of some production Microsoft ML inference applications (Lee et al., 2018). WILLUMP improves ML inference performance through two novel optimizations:
1) Automatic End-to-end Cascades: ML inference pipelines often compute many features for use in a model, but because ML applications are amenable to approximation, it is often possible to classify data inputs using only a subset of these features. For example, in a pipeline that detects toxic online comments, we may need to compute expensive TF-IDF vectorizations to classify some comments, but we can classify others simply by checking for curse words.

However, selectively computing features is challenging because features vary by orders of magnitude in computational cost and importance to the model and are often computationally dependent on one another. Therefore, one cannot pick an arbitrary set of features (e.g., the least computationally intensive) and expect to efficiently classify data inputs with them.

To address these challenges, WILLUMP uses a dataflow analysis algorithm and cost model to identify important but inexpensive features. With these features, WILLUMP trains an approximate model that can identify and classify “easy” data inputs. For example, an approximate model for toxic comment classification might classify comments with curse words as toxic and cascade other comments to a more powerful model. WILLUMP automatically tunes its own parameters to select the features that minimize expected query execution time while meeting a target accuracy level. The concept of model cascades has a long history in the ML literature (Viola & Jones, 2001), but to the best of our knowledge, WILLUMP is the first system to automatically generate feature-aware and model-agnostic cascades from input programs. WILLUMP’s cascades deliver speedups of up to 5× on real-world ML inference pipelines without a statistically significant effect on accuracy.

2) Top-K Query Approximation: WILLUMP automatically optimizes an important class of higher-level application queries: top-K queries. Top-K queries request a ranking of the K top-scoring elements of an input dataset (Cheng et al., 2016). They are fundamentally asymmetric: predictions for high-scoring data inputs must be more precise than predictions for low-scoring data inputs. Existing model serving systems such as Clipper or Pretzel perform these queries naively, scoring every element of the input dataset and thus wasting time generating precise predictions for low-scoring data inputs. WILLUMP instead leverages the asymmetry by automatically constructing a computationally simple approximate pipeline to filter out low-scoring inputs, maximizing performance while meeting a target accuracy level. Approximation improves performance on real-world serving workloads by up to 10×, with negligible impact on pipeline accuracy.

WILLUMP complements end-to-end cascades and top-K query approximation with powerful compiler optimizations. WILLUMP compiles a subset of Python to machine code through the Weld system (Palkar et al., 2017; 2018), in the process applying optimizations such as loop fusion and vectorization. Compilation improves query throughput by up to 4× and query latency by up to 400×.

We evaluate WILLUMP on a broad range of pipelines curated from entries to major data science competitions hosted by Kaggle, CIKM, and WSDM. Overall, WILLUMP improves query throughput by up to 16× and query latency by up to 500×. WILLUMP’s novel optimizations contribute greatly to this performance: end-to-end cascades improve performance by up to 5× and top-K query approximation by up to 10×. WILLUMP also improves the performance of other model serving systems; integrating WILLUMP with Clipper improves end-to-end query latencies by up to 10×. All performance improvements come without statistically significant accuracy loss.

In summary, we make the following contributions:

- We introduce WILLUMP, a statistically-aware end-to-end optimizer for ML inference pipelines.
- We automatically cascade feature computation, improving ML inference performance by up to 5× without statistically significant accuracy loss.
- We automatically approximate top-K queries, improving performance by up to 10× with minimal accuracy loss.

2 BACKGROUND

In this section, we provide background on ML inference pipelines, cascades, and top-K queries.

2.1 ML Inference Pipelines

WILLUMP optimizes ML inference applications whose performance is bottlenecked by feature computation. In such applications, ML inference is performed by a pipeline of transformations which receives raw inputs from clients, transforms them into numerical features, and executes an ML model on the features to generate predictions. In this paper we define features as numerical inputs to an ML model.

It is relatively common for ML inference applications to be bottlenecked by feature computation. For example, Pretzel’s study of ML inference at Microsoft found model execution accounted for as little of 0.3% of the runtime of some production ML inference pipelines (Lee et al., 2018). Many common operations in machine learning, such as querying data stores (Agarwal et al., 2014), behave like feature computation. Moreover, recent developments in automated machine learning (AutoML) on tabular data have increased the importance of feature computation. Researchers have developed algorithms such as Google AutoML Tables (Lu, 2019) and Deep Feature Synthesis (Kanter & Veeramachaneni, 2015) (whose open-source implementation is widely used (Kanter, 2018)) to automatically generate ML inference pipelines de-
Figure 1. A simplified toxic comment classification pipeline. The pipeline computes word- and character-level TF-IDF features from a string and predicts from them with a logistic regression model.

We diagram an ML inference pipeline in Figure 1. This pipeline, which we call toxic, is a simplified version of one of our real-world benchmark pipelines, taken from Kaggle. It predicts whether an online comment is toxic. toxic transforms an input string into numerical features with two TF-IDF vectorizers: one word-level and one character-level. toxic then executes a logistic regression model on these features to predict whether the input was toxic. In the real pipeline toxic is based on, model execution accounts for less than one percent of runtime; feature computation dominates.

2.2 Cascades

Cascades are an approximation technique for ML inference first developed for computer vision (Viola & Jones, 2001). ML inference is amenable to approximation because ML models return probabilistic predictions instead of exact answers. However, approximating naively incurs a high accuracy cost. Cascades reduce this accuracy cost for classification problems by leveraging differing data input difficulty.

In most classification workloads, many data inputs are “easy” to classify in the sense that a computationally simple model can accurately classify them (Viola & Jones, 2001). Therefore, a system need not approximate every data input. Instead, it can accurately classify easy data inputs with a computationally simple approximate model and cascade to a more expensive model for hard data inputs. Prior work such as NoScope (Kang et al., 2017) and Focus (Hsieh et al., 2018) has shown that cascades can dramatically improve model serving performance with minimal accuracy cost, but these systems are specialized to one model type.

Unlike prior cascades systems, WILLUMP automatically optimizes entire ML inference pipelines, training approximate models which depend on only a subset of the original model’s features. For example, an approximate model for toxic might compute only word-level (and not character-level) TF-IDF features. We call WILLUMP’s cascades optimization end-to-end cascades. We discuss it in more detail in Section 4.

2.3 Top-K Queries

Top-K queries are an important class of ML inference query. They request a ranking of the K top-scoring elements of a dataset. Top-K queries are especially common in recommender systems (Cheng et al., 2016). Database researchers have proposed several algorithms for approximating top-K queries (Theobald et al., 2004). However, these algorithms require scoring functions to be monotonic (Ilyas et al., 2008); this is rarely true for ML models. Some ML recommender systems use fast retrieval models to approximate top-K queries (Cheng et al., 2016), but they develop these models manually. Because such optimization is not automatic, existing ML model serving systems such as Clipper or Pretzel do not optimize top-K queries, instead naively scoring all elements of the input dataset. WILLUMP automatically approximates top-K queries, constructing an approximate model dependent on a subset of the original model’s features to identify and discard low-scoring inputs before ranking remaining inputs with the original model. We describe our approximation algorithm in detail in Section 4.

3 WILLUMP OVERVIEW

WILLUMP is an optimizer for ML inference pipelines. WILLUMP users write ML inference pipelines as functions from raw inputs to model predictions in a dialect of Python. Specifically, these functions must register model training, prediction, and scoring functions, must be written as a series of function calls, and must represent data using NumPy arrays, SciPy sparse matrices, or Pandas dataframes.

WILLUMP operates in three stages: dataflow, optimization, and compilation. We diagram WILLUMP’s workflow in Figure 2.
Figure 3. WILLUMP’s cascades optimization. WILLUMP attempts to predict data inputs using the approximate model, but cascades to the original model if the approximate model is not confident.

Dataflow Stage: WILLUMP’s dataflow stage converts an ML inference pipeline into a graph of transformations. Figure 1 is an example transformation graph. We discuss transformation graph construction in Section 5.1.

Optimization Stage: WILLUMP’s optimization stage applies its end-to-end cascades and top-K query approximation optimizations to the transformation graph. We discuss these optimizations in Section 4.

Compilation Stage: WILLUMP’s compilation stage transforms the optimized graph back into a Python function. In the process, it compiles some graph nodes to optimized machine code using the Weld system (Palkar et al., 2017). We discuss graph compilation in Section 5.2.

4 OPTIMIZATIONS

In this section, we describe WILLUMP’s core optimizations: automatic end-to-end cascades and top-K query approximation.

4.1 Automatic End-to-End Cascades

End-to-end cascades speed up ML inference pipelines that perform classification by classifying some data inputs with an approximate model dependent on a subset of the original model’s features. When using cascades, WILLUMP first attempts to classify each data input with the approximate model. WILLUMP returns the approximate model’s prediction if its confidence exceeds a threshold, which we call the cascade threshold, but otherwise computes all remaining features and classifies with the original model. We diagram this in Figure 3.

WILLUMP automatically constructs end-to-end cascades from an ML inference pipeline, its training data, and an accuracy target. First, WILLUMP partitions features into computationally independent groups and computes their computational cost and importance to the model. Then, WILLUMP identifies several sets of computationally inexpensive but predictively powerful features. For each selected set of features, WILLUMP trains an approximate model, chooses a cascade threshold based on the accuracy target, and uses these to estimate the cost of accurately making predictions using cascades with those features. WILLUMP constructs cascades using the selected set of features that minimizes this cost. We sketch this procedure in Algorithm 1 and discuss it in the remainder of this section. It works as follows:

Partitioning Features: The first step of constructing cascades is partitioning features into computationally independent sets, which we call feature groups. This is
To estimate a minimum of the objective, \( W \) partitions features into groups, \( W \) discretizes it. \( W \) can classify without cascading to the original model. \( h_s \) is computed using the cascade threshold, which we set later.

To estimate a minimum of the objective, \( W \) discretizes it. \( W \) searches for the set \( S \) that minimizes the objective given \( \text{cost}(S) = c_{\text{max}} \). Critically, this set cannot be better than the set that maximizes \( h_s \) given \( \text{cost}(S) \leq c_{\text{max}} \), which is the set from which one could train an approximate model with maximal accuracy given \( \text{cost}(S) \leq c_{\text{max}} \). Thus, discretization transforms the problem of globally minimizing the objective into the problem of maximizing approximate model accuracy given a cost constraint.

Unfortunately, determining approximate model accuracy for all combinations of feature groups is impractical. Instead, \( W \) estimates model accuracy using permutation importance. For each candidate \( c_{\text{max}} \), it selects the set \( S \) of feature groups with maximum sum of permutation importance given \( \text{cost}(S) \leq c_{\text{max}} \). This is a knapsack problem; we solve it with dynamic programming.

After selecting a set of feature groups for each \( c_{\text{max}} \), \( W \) trains an approximate model and chooses a cascade threshold. With these, \( W \) computes values of the objective and selects the globally optimal features. We discuss these steps next:

Training Approximate Models: \( W \) trains an approximate model from a selected set of feature groups by computing all selected features from the training set and training a new instance of the original model on them.

Choosing Cascade Thresholds: To choose the cascade threshold for an approximate model, \( W \) classifies every element in a held-out portion of the training set using both the approximate and original models, noting the confidences of the approximate model’s predictions. For example, \( i \) is the set, \( f_i \), the original model’s prediction \( s_i \), and the approximate model’s confidence \( c_i \). The cascade threshold \( t \) is the lowest value such that if we predict every data input \( i \) with \( s_i \) if \( c_i > t \) and \( f_i \), otherwise, accuracy on the held-out set would be above the accuracy target \( a_t \).

Selecting Optimal Features: Using the approximate models and cascade thresholds, \( W \) computes the objective from Equation 1 for each selected set of feature groups. \( W \) constructs cascades from the selected set of feature groups, and corresponding approximate model and cascade threshold, that minimizes the objective.

4.2 Top-K Query Optimization

In top-K queries, users request a ranking of the K top-scoring elements in a dataset. Top-K queries are fundamentally asymmetric; they must score high-scoring elements with more precision than low-scoring elements. \( W \) leverages this asymmetry to approximate top-K queries by filtering out low-scoring candidates with an approximate model, then ranking the remainder with the original model. \( W \) automatically trains these approximate models during model training. This requires four user-specified parameters: a distribution \( K \) of typical values of \( K \), a distribution \( N \) of typical values of the dataset size \( N \), an accuracy metric (by default precision), and a lower
bound $a_t$ on the accuracy of the approximation.

**WILLUMP** trains approximate models for top-K queries, like approximate models for cascades, on the set of feature groups with maximum sum of permutation importance given a maximum total cost $c_{\text{max}}$. To evaluate a top-K query, **WILLUMP** scores all dataset elements with the approximate model, then ranks the $r_S K$ top-scoring elements with the original model. **WILLUMP** grid searches candidate values of $c_{\text{max}}$ and $r_S$, choosing the values that minimize the expected execution time of a top-K query given the accuracy bound $a_t$. We write this objective as:

$$\min_S \text{cost}(S) \cdot N + (\text{cost}(F) - \text{cost}(S)) \cdot r_S \bar{K} \text{ s.t. } a > a_t$$

(2)

Here, $S$ is the selected set of features, $a$ is the accuracy of approximated queries, $F$ is the set of all features, $N$ and $\bar{K}$ are the means of $N$ and $K$, and $r_S$ is computed by the procedure described in the next paragraph.

Given a selected set of features, **WILLUMP** sets $r_S$, which determines the number of inputs ranked by the original model, to the smallest value that satisfies the accuracy bound $a_t$. It determines this value by executing sample top-K queries on a held-out portion of the training set. **WILLUMP** first trains an approximate model and scores all elements of the held-out set. It then draws many values $\bar{K}$ and $N$ from $K$ and $N$. For each pair $(K, N)$, it draws a sample of size $N$ from the held-out set and measures the accuracies of approximate top-K queries ranked by the sample with different values of $r_S$. **WILLUMP** chooses the smallest value of $r_S$ whose accuracy is 95% certain to be greater than $a_t$, 95% of the time (these thresholds can be changed by the user). Specifically, it chooses the smallest $r_S$ such that if we consider each sample’s outcome to be a Bernoulli random variable (where accuracy on the sample is either $\geq$ or $< a_t$), the 95% binomial proportion confidence interval of this variable is entirely above 95% accuracy.

Using this procedure, **WILLUMP** can compute $r_S$ and, therefore, the expected query execution time (Equation 2) for any selected set of features. **WILLUMP** grid searches values of $c_{\text{max}}$, selecting features and computing execution time for each candidate value. It ultimately approximates top-K queries using the selected features and corresponding $r_S$ value that minimize expected top-K query execution time given $a_t$.

## 5 WILLUMP API and Compilation

In this section we define the dialect of Python **WILLUMP** can optimize and describe how **WILLUMP** compiles it.

### 5.1 WILLUMP API and Graph Construction

**WILLUMP** can automatically optimize an ML inference pipeline implemented as a Python function which follows three rules. First, its training, inference, and scoring functions must be registered; for classification pipelines the inference function must return a confidence metric. This rule guarantees **WILLUMP**’s optimizations can be agnostic to model APIs. Second, every statement in the pipeline must be a function call; the final statement, whose output is returned, must be to the model prediction function. This rule guarantees **WILLUMP** can trace data flow. Third, the pipeline must represent all data as NumPy arrays, SciPy sparse matrices, or Pandas dataframes. This rule guarantees **WILLUMP** can marshal data to and from **Weld**. We show a simple example pipeline function using scikit-learn below:

```python
def toxic_comment_classification(strings):
    wf = word_vectorizer.transform(strings)
    cf = char_vectorizer.transform(strings)
    return predict(model, wf, cf)
```

If an ML inference pipeline conforms to the above rules, **WILLUMP** can use standard compiler techniques to parse it into a directed acyclic graph of transformations. Each function called by the pipeline becomes a node in the transformation graph. While parsing, **WILLUMP** checks these functions against a list of known functions which it can compile to **Weld**. If the function is on the list, **WILLUMP** marks it compilable, otherwise **WILLUMP** leaves it in Python.

### 5.2 Transformation Graph Compilation

After optimizing a transformation graph, **WILLUMP** compiles the nodes marked compilable to optimized machine code using **Weld** (leaving the remaining nodes in Python) and packages them back into a Python function. **Weld** (Palkar et al., 2018) is an intermediate representation (IR) and compiler for data processing operations. **Weld** implements many compiler optimizations over its IR, including loop fusion, data structure preallocation, and vectorization. These are similar to the compiler optimizations implemented by some existing model serving systems such as Pretzel (Lee et al., 2018). The set of operators **WILLUMP** can compile to **Weld** is extensible; users can add **Weld** IR for custom operators. **WILLUMP** compiles graphs in four stages:

**Sorting:** The first stage of compilation is to sort the transformation graph into an ordered list of nodes which minimizes the number of transitions between compilable nodes (which are executed in **Weld**) and Python nodes. This is desirable because each transition requires marshaling data between languages and because the **Weld** optimizer can apply powerful end-to-end optimizations, such as loop fusion, over large **Weld** blocks. **WILLUMP** sorts the graph topologically, then heuristically minimizes the number
We evaluate \textsc{W} and parameterized to use several different tokenizers, at CIKM, Kaggle, and WSDM. We demonstrate that: high-performing entries to major data science competitions calls to them in the appropriate places, packages the resulting the Python blocks and Weld drivers into a Python program.

Compilation: The final stage of compilation is to combine \textsc{W} and uncompiled Python code. After generating Weld code, \textsc{W} compiles drivers into Python C extensions, inserts \textsc{W} coalesces Weld and uncompiled Python code segments together, creating blocks of Weld and Python code. 

Drivers: The third stage of compilation is to generate a driver, a Python extension that calls into Weld, for each block of Weld code. \textsc{W} identifies each block’s input and output variables, then generates C++ driver code that marshals each block’s input variables into Weld data structures, executes its Weld code, and marshals its output variables into Python data structures. To minimize driver latency, we developed several new Weld types for \textsc{W}, including dataframe and sparse matrix types, which drivers can create in \O (1) time from their Python equivalents.

Compilation: The final stage of compilation is to combine the Python blocks and Weld drivers into a Python program. \textsc{W} compiles drivers into Python C extensions, inserts calls to them in the appropriate places, packages the resulting all-Python program as a Python function, and returns it.

6 Evaluation

We evaluate \textsc{W} and its optimizations on seven high-performing entries to major data science competitions at CIKM, Kaggle, and WSDM. We demonstrate that:

1. \textsc{W} improves batch inference throughput by up to \(16 \times\) and point query latency by up to \(500 \times\). Of this speedup, up to \(5 \times\) comes from end-to-end cascades.
2. \textsc{W} improves top-K query performance by up to \(31 \times\). Of this speedup, up to \(10 \times\) comes from top-K query approximation.
3. \textsc{W} improves the performance of other model serving systems. \textsc{W} improves end-to-end Clipper performance by up to \(9 \times\). Moreover, \textsc{W}’s optimizations improve performance over compiler optimizations similar to Pretzel’s alone\(^1\).

6.1 Experimental Setup

We ran all benchmarks on a Google Cloud instance with 4 Intel Xeon CPUs running at 2.20 GHz with 30 GB of RAM. We stored remote data tables on a Redis 3.2.6 server on a GCP instance with 1 Intel Xeon CPU running at 2.20 GHz with 30 GB of RAM in the same datacenter as the first instance.

6.2 Benchmarks

We benchmark \textsc{W} on the seven real-world workloads described in Table 1, all curated from entries in major data science competitions. All benchmarks are single-threaded. One benchmark, purchase, uses features automatically generated by the Deep Feature Synthesis algorithm (Kanter & Veeramachaneni, 2015); these features consist largely of aggregations such as averages and counts over relational data. Two benchmarks, credit and music, query data from stores which can be located either locally or remotely. We query music remotely in all benchmarks but query credit remotely only in top-K benchmarks because it performs regression and cannot be cascaded. We show all benchmarks’ transformation graphs in Figure 5.

6.3 End-to-end Evaluation

In this section, we evaluate the ability of \textsc{W} to improve the throughput and latency of ML inference queries.

\textsc{W} Throughput. We first evaluate \textsc{W} on offline batch queries, showing results in Figure 6. First, we apply \textsc{W}’s compiler optimizations. These improve the performance of all compilable benchmarks by up to \(4.3 \times\).

1\textsuperscript{We cannot compare against Pretzel directly as its code and benchmarks are not publicly available.
End-to-end cascades improve benchmark performance by up to 5×. Interestingly, cascades are least effective on music, which queries pre-computed features from an in-memory database. This is very fast when compiled, so feature computation accounts for a small portion of overall runtime and potential gains from cascades are limited. In music-remote, we moved the features to a remote database, so querying them was more costly and cascades became more effective, providing a 2.4× speedup.

**WILLUMP Latency.** We next evaluate WILLUMP on online point queries, showing results in Figure 7. We evaluate all benchmarks except purchase; the Python implementation of the deep feature synthesis algorithm was not designed for low-latency queries. When evaluating, we make one query at a time; each query contains one data input. We first apply WILLUMP’s end-to-end compiler optimizations to all compilable benchmarks. These decrease average and tail latency by 1.3-400×. The large speedup on music and credit is enabled by WILLUMP’s low-latency Weld drivers, which call into WILLUMP’s Weld code far faster than the benchmarks’ original Pandas implementations can call into their underlying C code; this is critical for point operations.

We then apply end-to-end cascades to all classification benchmarks. These improve average latency by up to 2.5× for most benchmarks. However, because cascades only speed up prediction of some data inputs (those classified by the approximate model), they do not improve tail latency. Cascades are least effective on product and music; in both cases this is because the latency contribution of feature computation is small compared to that of the model. We demonstrate this with an alternate version of music, music-remote, which queries features from remote databases instead of an in-memory store. As in the previous section, more expensive feature computation makes cascades more effective; they decrease average latency of music-remote by 2.5×.

**Top-K Queries.** We now evaluate WILLUMP on top-K queries, showing results in Figure 8. We use \( K = 20 \), query over the entire validation set, and set a minimum precision of 0.95.

We first apply WILLUMP’s end-to-end compiler optimizations to compilable benchmarks; these perform the same as in the batch setting. We then apply WILLUMP’s top-K query approximation optimization. This produces performance improvements ranging from 1.3-10× with precision always.
Integration with Clipper. We now evaluate integration of WILLUMP with Clipper, showing results in Figure 9. We optimize product and toxic with WILLUMP’s compiler and cascades optimizations and serve with Clipper, evaluating end-to-end query latencies. At a batch size of 1, WILLUMP improves average latency by 2.5-3× and tail latency by 4.5-12×. At a batch size of 100, WILLUMP improves average latency by 4.9× and tail latency by 5-25×. These speedups are slightly smaller than in prior experiments but increase with batch size because Clipper has significant overheads, including serialization, RPC processing time, etc.

6.4 Microbenchmarks

In this section, we analyze WILLUMP’s optimizations in detail.

Cascades Tradeoffs. We first examine the behavior of WILLUMP’s cascades optimization. For each classification benchmark, we graph performance and accuracy at varying cascade thresholds in Figure 10. On each graph, a blue circle marks the performance of the original model and an orange X that of the approximate model; points in between are cascaded models with varying cascade thresholds. As a reminder, the cascade threshold is the confidence the approximate model must have in a prediction to return the prediction and not cascade to the original model.

For all benchmarks, cascaded models with high cascade thresholds are faster than the original model but have similar accuracy. WILLUMP’s cascades algorithm automatically chooses these cascade thresholds to maximize performance without statistically significant accuracy loss. On each graph, the point marked with a red diamond is the chosen threshold.

For most benchmarks, as the cascade threshold decreases, performance continues to improve but accuracy falls off. This shows cascades are working as intended. At high cascade thresholds, the approximate model classifies easy data inputs and the original model classifies hard data inputs, so accuracy is high. At low thresholds, the approximate model must classify hard data inputs, so accuracy falls.

WILLUMP Overhead. We now evaluate WILLUMP’s overhead. First, we examine the training times of WILLUMP’s end-to-end cascades and top-K query approximation, showing results in Table 2. WILLUMP’s end-to-end training times are 1.0-4.9× as long as the end-to-end training times of the original pipelines. The increase in training time is largest for benchmarks whose end-to-end training
We find these rarely exceed thirty seconds. The exceptions we also evaluate W as an optimizer for ML inference pipelines, W written in high-level languages (most commonly Python) which Weld can query. (Crankshaw et al., 2017) and Rafiki (Wang et al., 2018), video datasets. Major web companies have also developed latency guarantees by dropping slow-to-compute features. signed for linear models used in advertising, which provides other tasks. Also related is LASER (Agarwal et al., 2014), de-...specialized systems for video recommendation (Davidson et al., 2010) and ad-targeting (Cheng et al., 2016), among other tasks. Also related is LASER (Agarwal et al., 2014), designed for linear models used in advertising, which provides latency guarantees by dropping slow-to-compute features. WLLUMP generalizes ideas from these application-specific systems, such as their use of cascades.

**Cascades:** Cascades were initially developed for rapid object detection by applying more complex classifiers to more object-like regions of an image (Viola & Jones, 2001). They have been widely applied to image and video tasks such as pedestrian detection (Cai et al., 2015) and face recognition (Sun et al., 2013). Some application-specific model serving systems, such as NoScope and Focus, utilize cascades. Researchers have proposed cascade algorithms, such as CSTC (Xu et al., 2014), which incorporate feature computational cost, but, unlike WLLUMP, they perform no graph or dataflow analysis, assume all features are computationally independent, require users to provide costs for all features, and require users to use a cascade of CART trees as their model.

**Top-K Approximation:** Database researchers have proposed many algorithms for optimizing and approximating top-K queries. These algorithms, including MPro (Chang & Hwang, 2002) and approximate TA (Theobald et al., 2004), among others (Ilyas et al., 2008), score candidates by querying one data source at a time; they drop candidates whose probability of scoring in the top K given the queried data sources is too low. However, they do not translate well to ML top-K queries. They assume that scoring functions execute on a set of data sources which can be queried independently, but ML models execute on features which are often computationally interdependent. They also assume that scoring is done by a monotonic and usually linear aggregation function, but ML models are typically nonlinear and offer no monotonicity guarantees.

Some systems for performing ML top-K queries use a retrieval model to select high-scoring inputs to rank with a more powerful model (Cheng et al., 2016). This is similar to WLLUMP’s use of an approximate model, but retrieval models are typically manually constructed while WLLUMP constructs approximate models automatically. Therefore, to the extent of our knowledge, WLLUMP is the first system to automatically optimize ML top-K queries.

**ML Optimizers and Compilers:** Several prior systems have developed optimizers and compilers for ML workloads. Unlike WLLUMP, many specialize in improving neural network performance. For example, TVM (Chen et al., 2018) compiles deep neural nets to different architectures and NVIDIA TensorRT (Sharma & Moroney, 2018) is a library optimized for fast inference performance on NVIDIA GPUs. Additional optimization techniques include knowledge distillation (Hinton et al., 2015) and approximate caching (Kumar et al., 2019). Some systems, like WLLUMP, optimize ML pipeline performance. For example, KeystoneML (Sparks et al., 2017) optimizes distributed training pipelines. Closer to WLLUMP is Pretzel (Lee et al., 2018), which improves ML inference performance through end-to-end compiler optimizations such as loop fusion and vectorization. These

| Table 2. Ratios of WLLUMP to Python training times when training end-to-end cascades and top-K query approximations. |
| Cascades | Music | Product | Instant | Purchase | Price | Credit |
|----------|-------|---------|---------|----------|-------|--------|
| WLLUMP   | 1.1x  | 4.9x    | 2.2x    | 1.0x     | 1.7x  | N/A    |
| Top-K    | 1.1x  | 4.8x    | 1.8x    | 1.0x     | 1.6x  | 3.8x   | 3.9x   |

**7 RELATED WORK**

**Model Serving:** Researchers and commercial vendors have developed many model serving systems. Some are general-purpose, serving different models from different frameworks. These include research systems, such as Clipper (Crankshaw et al., 2017) and Rafiki (Wang et al., 2018), and commercial platforms, such as Amazon’s Sagemaker and Microsoft’s Azure ML, among others (Olston et al., 2017; Apache, 2019). These systems aim to reduce the difficulty of deploying ML models. They deploy models in containers with an RPC frontend. They support models written in high-level languages (most commonly Python) using popular frameworks such as TensorFlow (Abadi et al., 2016) and MXNet (Chen et al., 2015). Typically, they consider models to be black boxes and implement only pipeline-agnostic optimizations such as end-to-end caching and adaptive batching (Crankshaw et al., 2017). However, recently researchers have developed more powerful optimizations, such as the use of erasure codes to improve accuracy in the face of unavailability (Kosaian et al., 2019).

As an optimizer for ML inference pipelines, WLLUMP synergizes with general-purpose model serving systems, significantly improving their performance with its novel statistically-aware optimizations, as we show in Section 6.3.

Other model serving systems are application-specific. For example, NoScope (Kang et al., 2017) and Focus (Hsieh et al., 2016) improve performance of neural nets querying large video datasets. Major web companies have also developed specialized systems for video recommendation (Davidson et al., 2010) and ad-targeting (Cheng et al., 2016), among other tasks. Also related is LASER (Agarwal et al., 2014), designed for linear models used in advertising, which provides latency guarantees by dropping slow-to-compute features.
are similar to the optimizations WILLUMP implements through Weld compilation, but unlike WILLUMP Pretzel does not implement ML-specific optimizations such as cascades or top-K approximations.

8 Conclusion

This paper presents WILLUMP, a statistically-aware end-to-end optimizer for ML inference. WILLUMP leverages unique properties of ML inference applications to automatically improve their performance through novel optimizations, including end-to-end cascades and top-K query approximation. WILLUMP improves the performance of real-world ML inference pipelines by an order of magnitude over existing systems.

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