Neural Query Language: 
A Knowledge Base Query Language for Tensorflow

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Abstract

Large knowledge bases (KBs) are useful for many AI tasks, but are difficult to integrate into modern gradient-based learning systems. Here we describe a framework for accessing soft symbolic databases using only differentiable operators. For example, this framework makes it easy to conveniently write neural models that adjust confidences associated with facts in a soft KB; incorporate prior knowledge in the form of hand-coded KB access rules; or learn to instantiate query templates using information extracted from text. NQL can work well with KBs with millions of tuples and hundreds of thousands of entities on a single GPU.

1 Introduction

Large knowledge bases (KBs) are useful for many AI tasks, but are difficult to integrate into modern gradient-based learning systems. Here we describe the Neural Query Language (NQL), a framework for accessing soft symbolic databases using only differentiable operators from Tensorflow [1]. NQL is a dataflow language, implemented in Python and Tensorflow, that provides differentiable operations over (sets of) entities and relations in a KB. NQL makes it easy to conveniently write neural models that perform actions that are otherwise difficult. For instance, a model can adjust confidences associated with facts in a symbolic KB; incorporate prior knowledge in the form of hand-coded KB access rules; learn new KB access rules, thus implementing a variant of inductive logic programming.

NQL can also be used in a system that will learn to answer natural-language queries against a KB in a fully end-to-end manner, trained using examples consisting of a natural-language query input and a entity-set output. For example, a question like “who was the father of Queen Victoria’s husband?” might require the following steps to answer:

1. Find the KB entity $e_1$ corresponding to “Queen Victoria” in a KB, and find the KB relations $r_1$ and $r_2$ that correspond the “husband” and “father of”.
2. Use the KB to find the entity or entities $e_2$ that are related to $e_1$ via the relationship $r_1$, and then find the entity or entities $e_3$ that are related to $e_1$ via the relationship $r_3$.

Neural networks can be trained to perform the first step above: finding $e_1$ is an entity-linking task and finding $r_1$ and $r_2$ is a relation extraction task. Using NQL, the second step can also be performed with differentiable operators. This means that the loss between the predicted answer (in this case $e_3$) and the desired answer can be backpropagated all the way to the entity-linking and relation extraction networks.

2 Related Work

NQL is closely related to TensorLog [2], a deductive database formalism which also can be compiled to Tensorflow. In fact, NQL was designed so that every expression in the target sublanguage used
by TensorLog can be concisely and readably written in NQL. TensorLog, in turn, has semantics
derived from other "proof-counting" logics such as stochastic logic programs (SLP) [3]. TensorLog is
also closely related to other differentiable first-order logics such as the differentiable theorem prover
(DTP) [5], in which a proof for an example is unrolled into a network. DPT includes representation-
learning as a component, as well as a template-instantiation approach similar to the one used in NQL.
TensorLog and NQL are more restricted than DPT but also more scaleable: the current version of
NQL can work well with KBs with millions of tuples and hundreds of thousands of entities, even on
a single GPU.

NQL however is not a logic, like TensorLog, but a dataflow language, similar in spirit to Pig [4]
or Spark [7]. NQL also includes a number of features not found in TensorLog, notably the ability
to have variables that refer to relations. NQL also makes it much easier for Tensorflow models to
include pieces of NQL, or for NQL queries to call out to Tensorflow models.

NQL is one of many systems that have been built on top of Tensorlog or some other deep-learning
platform. Perhaps the most similar of these in spirit is Edward [6], which like NQL, attempts to add
a higher-level modeling language based on a rather different programming paradigm: most other
packages are aimed at providing additional support for training, or combining existing Tensorflow
operators into reusable fragments. In the case of Edward, the alternative paradigm being supported is
probabilistic programming (e.g., variational autoencoder modes), while in Tensorlog, the alternative
paradigm supported is dataflow operations on KGs.

3 NQL: A Neural Query Language

3.1 Preliminaries

NQL allows one to query a KB of entities and relations. An (typed) entity e has a type type(e), and
an index i(e), which is an integer between 1 and N_{type(e)}, where N_\tau is the number of entities of type
\tau. Types and entities both have names, which are readable strings describing them: the name of an
entity e, for instance, will be written name(e) below. We assume that names and indices for entities
are unique within a type, so if type(e) = type(e') and either i(e) = i(e') or name(e) = name(e'),
then it must be that e = e'.

A weighted relation \pi with domain type \tau_1 and range type \tau_2 is a weighted multiset of pairs of entities
(e_1, e_2) such that type(e_1) = \tau_1 and type(e_2) = \tau_2. NQL currently supports only binary relations.
Relations can be thought of as weighted edges from nodes of type \tau_1 to nodes of type \tau_2. A weighted
relation \pi can be encoded as a (possibly sparse) matrix M_\pi \in \mathbb{R}^{N_{\tau_1} \times N_{\tau_2}}. Relations also have string
names.

A KB is a pair (\Pi, E) where \Pi = \pi_1, \ldots, \pi_{N_\Pi} is a set of relations, and E is a set of typed entities.
NQL also makes use of weighted multisets of typed entities. A weighted multiset \sigma of type \tau is a
mapping from entities of type \tau to non-negative real numbers, which we will write in a Python-like
notation, e.g. \{blue:0.9, red:1.0\}. Entities of type \tau not explicitly listed in this notation are
assumed to map to zero. A weighted multiset \sigma of type \tau can be encoded as a (possibly sparse) vector
v_\sigma \in \mathbb{R}^{N_\tau}, where v_\sigma[i(e)] = \sigma(e).

3.2 Simple NQL expressions

NQL is a simple KB query language embedded in Python. Some NQL expressions are produced using
an NQL context object, which contains pointers to a KB. Below I will use the variable c for an NQL
context object, and assume it has been initialized with a database derived from a widely-used example
database of genealogy information about European royal families[1] from which we have derived 12
familial relations named aunt, brother, daughter, father, husband, mother, nephew, niece, sister,
son, uncle, and wife. This KB has only one type, person_t, and all the relations/edges have unit
weight.

One can create singleton, unit-weighted sets using a call to c.one, for example:

```python
    henry8 = c.one(‘Henry_VIII of house of Tudor’, ‘person_t’)
```

[1]The dataset is widely distributed as an example of the GED format, for example under https://github.com/jdfekete/geneaquilt
### Table 1: Matrix-vector implementation for NQL operators. Vectors s, t, r correspond to s, t, r respectively, r is over the relation group π₁, ..., πₖ, and Mₜ corresponds to the relation rel.

| NQL expression | Vector-matrix specification | Comments |
|-----------------|-----------------------------|----------|
| s.rel()         | sₚ                           |          |
| s.rel(-1)       | sₚₜ                           |          |
| s | t     | s + t                         |          |
| s & t           | s ⊙ t                         | ◦ is Hadamard product |
| s.follow(r)     | s \left( \sum_{i=1}^{k} r[i] M_{π_i} \right) |          |
| s.if.any(t)     | s[t]₁                        | a is a Tensorflow scalar |
| s * a           | sa                            |          |

Evaluating and printing the NQL expression henry8 would yield the multiset \{'Henry VIII of house of Tudor': 1.0\}. There are two other primitive set-construction methods for contexts, c.none, which creates an empty set of a given type, and c.all, which creates a universal unit-weighted set of a given type.

Every relation π can be accessed by simply using the name of that relation as a method of any multiset-valued expression. For instance henry8.wife() would evaluate to a set of six people, \{'Anne of house of Boleyn':1.0, 'Anne of Cleves':1.0, ..., 'Jane of house of Seymour':1.0\}. Relations can also be chained: for example, the set of sons of Henry VIII’s daughters could be written as henry8.daughter().son().

One can also reference a relation by a string “r” that names it with the syntax s.follow('r'): for instance henry8.follow('wife') gives the same set as above. The inverse of a relation can by accessed by adding an argument -1 to a relation-name method: for example, Henry VIII’s parents could be found with the expression henry8.son(-1).

Unions and intersections of multisets of the same type can be computed using the operators “|” for union and “&” for intersection. For example, the set of henry VIII’s grandsons could be written as (henry8.son() | henry8().daughter()).son().

Since the language is embedded in Python, one can use Python’s function definition construct to define NQL functions. As an example, this definition

```python
def child(x): return son(x) | daughter(x)
```

would allow one to re-express the set defined above as child(henry8).son(). (One can also define new multiset methods, so that the notation henry8() could be used, by subclassing the NQL class.)

### 3.3 Conditionals, Predicate Variables, and Rule Templates

NQL also has a conditional construct. If s and t are multisets then s.if.any(t) returns exactly the set s if t is a singleton multiset with weight one on its only element, and returns the empty set if t is an empty set. More generally, s.if.any(t) will return a copy of s in which every element has been multiplied by a factor f, where f is the sum of all the weights of the members of t. This operation is best described using the vectors s and t corresponding to s and t respectively: the vector s' corresponding to s.if.any(t) is simply s' ≡ s[t]₁. This definition, along with the definitions of

![Figure 1: Example: Using NQL to compute the six wives (b) and twelve in-laws (c) of King Henry VIII (a). The variable sess is bound to a Tensorflow Session object.](image)
the other NQL operators, is shown in Table 1. It is also possible to obtain a similar conditional effect with the notation \( s \ast a \) where \( a \) is a Tensorflow scalar.

NQL also includes a construct which allows one to construct variables which range over relations. Any set of relations \( \pi_1, \ldots, \pi_k \) with the same domain and range types can be gathered together into relation group \( g \). This creates a new type \( \tau_g \) with \( N_{\tau_g} = k \) elements, whose entity members have the same names as the relations \( \pi_1, \ldots, \pi_k \). One can then use the same NQL constructs to create weighted multisets of relations.

For example, the \( \text{rel}_t \) is a type for all of the relations in this KB, one could create the multiset

\[
\text{child} = \text{c.one('daughter', 'rel_t')} \mid \text{c.one('son', 'rel_t')}
\]

If \( r \) is a multiset of relation-naming entities, then the syntax \( s.\text{follow}(r) \) also lets you “follow” a group of relations. So in this example, \( \text{henry8.\text{follow}(child)} \) would evaluate to the set of all daughters and sons of Henry VIII. More generally, the weights associated with each relation in \( r \) are combined multiplicatively with any weights associated with the edges in the KB itself: a definition for this operator is also shown in Table 1.

4 Learning and Rule Templates

4.1 NQL and Tensorflow

NQL is tightly integrated with Tensorflow. Every NQL expression is attached to a context object \( c \). The context object has sufficient information to produce an appropriate Tensorflow compute-graph node which is an implementation of the NQL expression. These Tensorflow expressions are computed bottom-up.

If \( x \) is an NQL expression, one can access the underlying Tensorflow implementation using the syntax \( x.\text{tf} \). If \( \tau \) names an NQL type and \( c \) is an NQL context, and if \( w \) is a compatible Tensorflow \text{Tensor} or \text{Variable} object, then \( c.\text{as_nql}(w, \tau) \) converts \( w \) to an NQL expression. (By “compatible” here we mean that \( w \) contains a tensor of the right shape, i.e., it contains a minibatch of vectors in \( \mathbb{R}^{N_{\tau}} \).) This makes it relatively simple to convert back and forth between NQL and Tensorflow, so models can easily include Tensorflow submodels (e.g., an LSTM to encode represent text) as well as NQL templates.

The current implementation of NQL can handle KBs with a few million tuples and types with a few hundred thousand entities on a single commodity GPU.

4.2 Learning with NQL

Having variables that can be bound to multisets of relations makes it possible to write relatively generic “template” queries. For instance, in the family-relations domain, many of the relations can be approximated with the union of a small number of queries that each chain together two other relations: e.g., \( x.\text{father()} \) is approximately the same as \( x.\text{mother().husband()} \), and \( x.\text{daughter()} \) is approximately the same as \( x.\text{daughter().sister()} \mid x.\text{son().sister()} \).

If one wanted to learn to approximate a new familial relation with the ones in this dataset, one might pose the following learning problem: learn values for the multiset relation variables \( r_1, r_2, r_3 \) and \( r_4 \) for the query:

\[
x.\text{follow}(r_1).\text{follow}(r_2) \mid x.\text{follow}(r_3).\text{follow}(r_4)
\]

This “template” could be turned into an approximation of \( \text{father} \) by setting \( r_1=r_3=\{\text{mother}:1.0\} \), \( r_2=r_4=\{\text{husband}:1.0\} \), or into an approximation of \( \text{daughter} \) by setting \( r_1=\{\text{daughter}:1.0\} \), \( r_3=\{\text{son}:1.0\} \), \( r_2=r_4=\{\text{sister}:1.0\} \). Templates reduce the difficult problem of searching a discrete space of possible queries to the more tractable problem of searching a continuous space of weights inside a multiset.

Using this template, a very minimal approach to learning rules for an unknown predicate \( \pi_* \) would be the following. (We assume the rules will take as input a domain entity \( x \) and output a set of things related to \( x \) via \( \pi_* \).) First, let \( r_1, \ldots, r_4 \) be NQL relation variables derived from Tensorflow Variables with shape \( k \), where \( k \) is the number of relations. Second, let the models prediction \( y \) be defined using the template above, i.e., let
Input: an entity \( x \); Output: entity-set \( y \) so that \( y = \{ y' : \pi(x, y) \} \)

```python
def trainable_rel_var():
    return c.as_nql(tf.Variable(tf.ones_initializer()[:k]))
r1 = trainable_rel_var()
r2 = trainable_rel_var()
r3 = trainable_rel_var()
r4 = trainable_rel_var()
y = x.follow(r1).follow(r2) | x.follow(r3).follow(r4)
loss = \( \ell(y, tf, target\_labels) \)
```

### Table 2: Some example learning based on NQL templates. In each of these the \( f \)'s are differentiable functions of a textual query \( q \), e.g., based on an encoder-decoder approach.

Input: a question \( q \) containing an entity \( e \) Output: entity-set \( y \) answering the question \( q \).

```python
rel = c.as_nql(f(q))
y = e.follow(rel)
loss = \( \ell(y, tf, target\_labels) \)
```

Input: a question \( q \) containing an entity \( e \) Output: entity-set \( y \) answering the question \( q \).

```python
r1 = c.as_nql(f1(q))
r2 = c.as_nql(f2(q))
switch1 = f3(q)
switch2 = f4(q)
y = e.follow(r1) * switch1 | e.follow(r1).follow(r2) * switch2
loss = \( \ell(y, tf, target\_labels) \)
```

Input: an initial entity \( e \) and encoded state \( s \); Output: entity-set \( y \)

```python
p = 1; y = tf.zeros(k)
for i in range(MAX_HOPS):
s, r, p_stop = f(s)
e = e.follow(r)
y += p * p_stop * e.as_tf()
p = p * (1 - p_stop)
```

### Table 3: An example learning using NQL without templates. Here \( f \) is a recurrent, differentiable function of a state vector \( s \) which returns a new state vector \( s \), a distribution over relations \( r \), and a probability of stopping \( p \).

Third, define an appropriate loss function on \( y \) and train. This learns a definition of the predicate in terms of the values of \( r1, \ldots, r4 \). This approach is summarized on the top of Table 2.

Another example use of templates is for question-answering against a KB. For example, consider simple questions of the form “Who was the father of Queen Victoria?” which ask for entities in some particular relation (e.g., father) to a specific “seed entity” \( e \) appearing in the question (e.g., ‘Victoria of house of Hanover’). If there is an entity-linking system that can extract the appropriate entity \( e \) from a question \( q \), then a simple question-answering system can be defined using the model in the second panel of Table 2. Here \( f \) would be an arbitrary differentiable function of \( q \), e.g., based on decoding an LSTM to the relation variable.

Clearly, these approaches could be combined to construct models for more complex, multi-hop, compositional queries, like “who was the father of Queen Victoria’s husband?”, as shown in the bottom panel of Table 2. Here \( f_1, \ldots, f_4 \) are based on decoding \( q \), and \( switch1 \) and \( switch2 \) are “switches” which select whether a one-hop or two-hop query was selected.

### 4.3 Learning without Templates

Consider the question answering task described at the end of Section 4.2 with a given seed entity \( e \) and potentially multiple relations necessary to reach the target. As shown above this task can be learned using templates. However, this can grow unwieldy as the depth of reasoning increases.
Instead, one could take advantage of the structure inherent in these templates and build a model which learns over an entire family of templates. Each of the templates mentioned in the question answering task represents a series of relations followed sequentially where the relations to follow and the order to follow them in are what the model is learning.

We can use a recurrent model to predict any chain of relations up to an arbitrary length. Consider a recurrent model \( s_i, r_i, p_i = f(s_{i-1}) \) where \( s_i \) is the state at step \( i \), \( r_i \) is a predicted relation for step \( i \), \( p_i \) is the probability of stopping at step \( i \), and \( s_0 \) is an encoding of the query.

Using this model a final prediction can be calculated by weighting predictions from all number of steps up to some maximum as shown in Table 3.

Representing the problem in this way has the advantage that it allows for generalization to questions which require deeper reasoning than seen at training time. For example, a model trained on data which requires following up to 5 relations may successfully return answers requiring 6 or more relations to be followed.

This approach may be extended further to cover other more complex families of templates.

5 Advantages and Disadvantages of NQL

5.1 NQL vs. TensorLog

NQL’s implementation is fairly thin: it is implemented by having NQL expressions converted directly to Tensorflow computation graphs. During this conversion process NQL also enforces type checking (e.g., to ensure that the \( \tau \)’s for the domain and range of each relation is consistent). The eval method for NQL expressions makes use of backpointers to the context to allow conversion to the symbolic names of entities.

As Table 1 shows, NQL’s operations can be concisely specified with matrix-vector computations: it might be asked how much additional value the NQL abstraction provides over Tensorflow. We should note that the actual implementation of NQL’s operators are less concise than the specification, for a number of reasons. There are also a number of plausible ways to implement the \( s . f o l l o w ( r ) \) operation, and using this higher-level notation allows one to choose between them easily as a configuration option.

5.2 NQL vs. SQL (or SPARQL or OWL or ....)

Compared to more traditional KB query languages, NQL has a major limitation, in that it cannot construct and return tuples, only weighted sets of entities. This is a direct consequence of the decision to base NQL on differentiable vector-matrix operations, which do not support creating new objects (such as tuples).

This limitation seems to make it impossible for NQL to perform a number of familiar DB operations, such as joins. Consider two tables student and grade, student having fields id, program, and expected_degree and grade having fields student_id, course_id, letter_grade. Consider an SQL join query like

```
SELECT grade.id FROM student, grade
WHERE student.id = grade.student_id
AND student.expected_degree = 'PhD' AND grade.letter_grade = 'C'
```

which asks for PhD students that have gotten a C in some course. Although this seems to need more power than NQL has, it can be emulated by incorporating into the KB new structures which act as indexes for the relations. In this case, one could construct a student_record type and a grade_record type, and define relations such as student_record_id, mapping student_record entities to the appropriate id value, and so on. The SQL query above could be emulated with the NQL code

\[<\text{NQL code}>\]

\[<\text{Note: NQL code snippet suppressed for brevity}>\]

\[\text{Footnote: For instance, for even a small KB, it is essential that the } M_{\tau} \text{ matrices are stored as sparse matrices, but currently Tensorflow does not support sparse-sparse matrix multiplication, and multiplication of sparse matrix to a dense matrix is only supported in one order.} >\]
c_records = c.one('C', 'letter_grade_t').grade_record_letter_grade(-1)
records_of_students_with Cs = c_records.grade_record_student_id().student_record_id(-1)
records_of_phds = c.one('PhD', 'degree_t').student_record_expected_degree(-1)
result = (records_of_students_with Cs & records_of_phds).student_record_id

Although many join-like queries can be treated this way, SQL queries that return novel tuples clearly cannot be performed in NQL (e.g., if we modified the query above to select both a course id and a student id.) However, NQL has an advantage over more expressive query languages in that it is differentiable, so it is possible to base a differentiable loss function on the result of executing an NQL query.

6 Conclusion

We have described NQL, a query language which makes it convenient to integrate queries on a KB into a neural model implemented in Tensorflow. NQL accesses data using only differentiable operators from Tensorflow, which allows a tight integration with gradient-based learning methods. NQL is available as open source: because of its many applications in NLP, code for NQL is available at https://github.com/google-research/language, the Google Research repository for NLP components.

References

[1] Martín Abadi, Paul Barham, Jianmin Chen, Zhifeng Chen, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Geoffrey Irving, Michael Isard, et al. Tensorflow: A system for large-scale machine learning. In 12th {USENIX} Symposium on Operating Systems Design and Implementation ({OSDI} 16), pages 265–283, 2016.
[2] William W Cohen, Fan Yang, and Kathryn Rivard Mazaitis. Tensorlog: Deep learning meets probabilistic dbs. arXiv preprint arXiv:1707.05390, 2017. To appear in JAIR.
[3] James Cussens. Parameter estimation in stochastic logic programs. Machine Learning, 44(3):245–271, 2001.
[4] Alan F Gates, Olga Natkovich, Shubham Chopra, Pradeep Kamath, Shravan M Narayananmurthy, Christopher Olston, Benjamin Reed, Santhosh Srinivasan, and Utkarsh Srivastava. Building a high-level dataflow system on top of map-reduce: the pig experience. Proceedings of the VLDB Endowment, 2(2):1414–1425, 2009.
[5] Tim Rocktäschel and Sebastian Riedel. Learning knowledge base inference with neural theorem provers. In NAACL Workshop on Automated Knowledge Base Construction (AKBC), 2016.
[6] Dustin Tran, Alp Kucukelbir, Adji B Dieng, Maja Rudolph, Dawen Liang, and David M Blei. Edward: A library for probabilistic modeling, inference, and criticism. arXiv preprint arXiv:1610.09787, 2016.
[7] Matei Zaharia, Mosharaf Chowdhury, Michael J Franklin, Scott Shenker, and Ion Stoica. Spark: Cluster computing with working sets. HotCloud, 10(10-10):95, 2010.