



kogito: A Commonsense Knowledge Inference Toolkit

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Abstract

In this paper, we present **kogito**, an open-source tool for generating commonsense inferences about situations described in text. **kogito** provides an intuitive and extensible interface to interact with natural language generation models that can be used for hypothesizing commonsense knowledge inference from a textual input. In particular, **kogito** offers several features for targeted, multi-granularity knowledge generation. These include a standardized API for training and evaluating knowledge models, and generating and filtering inferences from them. We also include helper functions for converting natural language texts into a format ingestible by knowledge models — intermediate pipeline stages such as knowledge head extraction from text, heuristic and model-based knowledge head-relation matching, and an ability to define and use custom knowledge relations. We make the code for **kogito** available at <https://github.com/epfl-nlp/kogito> along with thorough documentation at <https://kogito.readthedocs.io>.

1 Introduction

In recent years, large-scale language models (Radford and Narasimhan, 2018; Devlin et al., 2019; Brown et al., 2020) trained on massive amounts of text have been conceptualized as implicit knowledge bases that encode knowledge about the world (Petroni et al., 2019; Roberts et al., 2020). As they are trained to receive natural language inputs, these models can be prompted to generate text that expresses a fact. Leveraging this property, *knowledge models* train on knowledge graph tuples (triplets of *head entity*, *relation*, *tail entity*) and learn to express knowledge encoded in the parameters of language models when provided with a *head entity* and *relation* (Bosselut et al., 2019; Hwang et al., 2021; Da et al., 2021; West et al., 2022).

The success of these *knowledge models* has inspired the field to deploy them in various down-

stream use-cases such as generating figurative language (Chakrabarty et al., 2020b), producing sarcastic responses (Chakrabarty et al., 2020a), designing plots for stories (Ammanabrolu et al., 2021) and text-based games (Dambekodi et al., 2020), and developing persona-grounded dialogue agents (Majumder et al., 2020). Given the prevalence of applications that benefit from augmenting NLP systems with commonsense inferences, we present a novel commonsense **KnOwledGe Inference TOolkit**, **kogito**, that standardizes commonsense inference generation from knowledge models. To the best of our knowledge, **kogito** is the first library that facilitates access to knowledge models through an easy-to-use, customizable interface. In particular, we make the following contributions:

1. A Python package¹ for knowledge inference with a customizable and extensible API.
2. A module to perform commonsense inference with a library of pretrained models, including GPT-2 (Radford et al., 2019), GPT-3 (Brown et al., 2020) and COMET (Hwang et al., 2021).
3. A standardized interface to train, evaluate and predict with knowledge models.
4. Modules to extract relevant candidates for commonsense inference (*i.e.*, head extraction) with support for customization and extension.
5. Modules to match relevant relations to extracted head entities (*i.e.*, relation matching) with support for customization and extension.
6. A module to filter commonsense inferences based on their contextual relevance using commonsense fact linkers (Gao et al., 2022)
7. Functionality to define novel knowledge relations on top of the built-in ATOMIC2020

¹<https://pypi.org/project/kogito/>

(Hwang et al., 2021) and ConceptNet (Speer and Havasi, 2013) relation sets.

8. Extensive documentation with User Guides and API Reference.²

The library is released under the Apache 2.0 License. We provide a demo video³ for our library along with a live demo app.⁴ Below, we outline the commonsense inference challenges addressed by this tool, its core design, and walk through its major components in more detail.

2 Challenges of Commonsense Inference

While many works use *knowledge models* as commonsense inference engines to augment natural language inputs, no work has formalized the pipeline for producing such inferences. Here, we outline the challenges of effectively setting up this pipeline.

Head Extraction Head extraction (*i.e.*, finding relevant concepts to produce commonsense inferences about) is a consistent challenge when using knowledge models. Typically, these inferences must be produced for more fine-grained textual units than full contexts (Bosselut et al., 2021). For instance, to understand figurative language, Chakrabarty et al. (2020b) extract concepts from similes such as "*Love is like a unicorn*". Commonsense inferences are generated about entities such as "*unicorn*" (*e.g.*, unicorns are *rare, beautiful*, etc.), allowing them to produce literal interpretations of this figurative language: "*Love is rare*". This use case motivates a need for fine-grained text extraction functionality in our tool. In Section 5, we outline our approach to address this challenge.

Relation Matching To generate commonsense inferences, knowledge models typically take as input a (*head, relation*) pair and produce a *tail* (*i.e.*, the commonsense inference about the *head* entity). Following this convention, once we have extracted candidate *heads* from a given text, they must be paired with relevant relations to produce valid commonsense inferences. For example, a head entity such as "go to mall" should not be paired with an *ObjectUse* relation as it is unlikely to produce a valid (and practical) commonsense inference. Consequently, a brute-force approach of matching all

relations to presented head entities would be inadequate for most use cases. Current works often circumvent this challenge by manually selecting only a subset of available knowledge relations. As part of *kogito*, we implement various heuristic and model-based matching schemes to address this challenge, while also providing users with the ability to define their own matching mechanisms. We discuss these implementations in Section 6.

Inference Generation & Filtering Once a list of relevant (*head, relation*) pairs is produced, we run these examples through a knowledge model to generate tail entities about these examples. However, many of these generated inferences may not be relevant to the original context, particularly for extracted head entities that have been decontextualized. *kogito* leverages a model-based approach (Gao et al., 2022) to filter out irrelevant commonsense generations. While other works reimplement pipelines for performing these steps, *kogito* offers an all-in-one solution.

3 kogito: A Pipeline for Commonsense Inference

kogito is a pipeline for commonsense inference from text and supports various steps to specialize and customize inference behaviour. At full functionality, given a text input, *kogito* extracts relevant *knowledge heads* from textual inputs, and matches these heads to plausible *knowledge relations*, thereby constructing an incomplete *knowledge graph* of (*head, relation*) prompts. Then, this partial graph is input to a *knowledge model* to generate tails to complete the graph. Finally, these commonsense inferences (comprised of the *head, relation*, and *tail*) are filtered based on their relevance to the initial context. Below we provide a simple example of how this module can be used to generate commonsense inferences for the example "*PersonX becomes a great basketball player*":

```
from kogito.models.bart.comet import COMETBART
from kogito.inference import CommonsenseInference

# Load pre-trained model from HuggingFace
model = COMETBART
        .from_pretrained("mismayil/comet-bart-ai2")

# Initialize inference module
csi = CommonsenseInference()

# Run inference
text = "PersonX becomes a great basketball player"
kgraph = csi.infer(text, model)

# Save output knowledge graph to JSON file
kgraph.to_jsonl("kgraph.json")
```

²<https://kogito.readthedocs.io/>

³<https://www.youtube.com/watch?v=rFGzDrLCx00>

⁴<https://kogito.live>

The resulting knowledge graph from the code above contains inferences such as "*PersonX needs to practice a lot*" and "*PersonX is athletic*". Various parts of this pipeline can be customized and modified, allowing users to define their own modules. In the following sections, we discuss `kogito`'s core design, as well as the *head extraction*, *relation matching*, and *inference filtering* components of the pipeline. More details on these configuration options can be found in the `kogito` documentation.

4 Data Representation

To allow for standardization and ease of maintenance, `kogito` defines an interface to represent core concepts such as a *knowledge tuple*, a *commonsense knowledge graph*, and a *knowledge model*.

Commonsense Knowledge Tuple Commonsense knowledge graphs (Speer and Havasi, 2013; Hwang et al., 2021) and knowledge models (Bosse-lut et al., 2019) typically represent instances of knowledge as tuples of 3 elements: (*head*, *relation*, *tail*). The *head* entity refers to the subject of a piece of knowledge (e.g., objects such as *hammer*; events such as "*PersonX becomes a great basketball player*"). A *relation* provides an implicit question about the *head* (e.g., *CapableOf* → *what is this head entity capable of?*; *xNeed* → *What does PersonX need before this event occurs?*). Finally, *tail* entities provide an answer option (among potentially many) to the relation with respect to the head (e.g., *put nail in wood*; *to practice hard*). We often refer to the *tail* as the commonsense inference about the *head*.

Following this convention, we define a class with these elements and an additional two classes for knowledge *head* and *relation* representation. While knowledge *heads* and *tails* can be arbitrary text, we use predefined *relations* from the ATOMIC2020 (Hwang et al., 2021) and ConceptNet (Speer and Havasi, 2013) knowledge graphs.⁵ Below is an example of defining a knowledge tuple in `kogito`:

```
from kogito.core.head import KnowledgeHead
from kogito.core.knowledge import Knowledge
from kogito.core.relation import X_NEED

head = KnowledgeHead("PersonX becomes a great
                    "basketball player")
kg = Knowledge(head=head, relation=X_NEED,
              tails=["practice hard"])
```

Knowledge Graph In addition to individual knowledge tuples, we also define a knowledge

graph as a collection of knowledge tuples. In `kogito`, a knowledge graph serves as the standardized input object to (and output from) knowledge models, and has a simple API to manipulate knowledge instances collectively. In particular, a knowledge graph can be used to easily iterate over, read, and write a collection of knowledge instances to and from various files, and perform set-like operations on multiple knowledge graphs. These operations require a notion of equality, so we define two knowledge instances to be equal if they have the same head, relation and tail. Below is an example of defining and manipulating knowledge graphs:

```
from kogito.core.knowledge import KnowledgeGraph

# Read from csv
kgraph1 = KnowledgeGraph
    .from_csv("sample_graph1.csv",
             sep="|", header=None)

# Read from jsonl (list of json objects)
kgraph2 = KnowledgeGraph
    .from_jsonl("sample_graph2.jsonl",
               head_attr="source",
               relation_attr="rel",
               tails_attr="targets")

# Union
# kgraph1.union(kgraph2)
kgraph3 = kgraph1 + kgraph2

# Intersection
# kgraph1.intersection(kgraph2)
kgraph3 = kgraph1 & kgraph2

# Difference
# kgraph1.difference(kgraph2)
kgraph3 = kgraph1 - kgraph2

# Write to jsonl
kgraph3.to_jsonl("sample_graph3.jsonl")
```

Knowledge Model Knowledge models conceptually accept as input a (*head*, *relation*) pair and output an inferred knowledge tail. However, these models can sometimes expect a subtly different formats for these inputs and outputs. To increase the extensibility and interoperability of our tool, so that users can easily substitute one knowledge model for another, we define a model-agnostic abstraction over possible types of knowledge models. Consequently, knowledge models inherit from an abstract interface that defines core abstract methods, which users can implement to port new knowledge models into `kogito`. The *knowledge model* interface provides methods to train, generate from, evaluate these models, as well as save and load them. The input dataset for training, generating, or evaluating is given as a *knowledge graph* and the output dataset (in the case of generation) is returned as a *knowledge graph*.

`kogito` currently offers the following knowledge models: COMET-BART and COMET-GPT2

⁵`kogito` also supports defining new custom relations and using them to generate commonsense inferences (§8)

from Hwang et al. (2021), GPT2-zeroshot (Radford et al., 2019), and GPT3-zeroshot (Brown et al., 2020). Pre-trained COMET models can be loaded either from HuggingFace⁶ by name or from local disk by model path. The GPT-3 model requires an API key. Each model method supports customization of various model-specific hyperparameters. `kogito` currently evaluates models using the following metrics: *BLEU* (Papineni et al., 2002), *ROUGE* (Lin, 2004), *METEOR* (Lavie and Agarwal, 2007), *CIDEr* (Vedantam et al., 2015) and *BERTScore* (Zhang et al., 2019).

Pipeline Design In the following sections, we discuss the *head extraction*, *relation matching*, and *inference filtering* components of this pipeline. We note that we provide a “dry-run” mode which allows for faster iteration on head extraction and relation matching by skipping the inference generation portion of `kogito`’s pipeline. More details on these configuration options can be found in the `kogito` docs.

5 Head Extraction

Head extraction refers to finding relevant chunks of a text in a sequence that can serve as knowledge heads (*i.e.*, the concepts commonsense inferences should be generated about). For example, given a text input “*PersonX becomes a great basketball player*”, we might be interested in generating inferences for the full sentence, but also about entities such as “*basketball player*”, “*basketball*”, or potentially “*become player*”. For different applications, different sets of head entities might be appropriate for generating inferences. Consequently, `kogito` allows the user to customize this behaviour and define arbitrary head extraction methods.⁷

At the same time, by default, `kogito` comes with a few standard head extraction methods. These built-in methods segment sentences, and then extract noun phrases (NP) and verb phrases (VP) using dependency parses produced from `spaCy`.⁸ Extracted heads are deduplicated using string matching and passed onto the next stage of the pipeline, *relation matching*. We note that the *head extraction* stage itself is optional and the user can also provide a dedicated list of heads to `kogito`, which would replace the pre-processing of head entities.

⁶<https://huggingface.co/models>

⁷<https://tinyurl.com/head-extraction>

⁸<https://spacy.io/>

6 Relation Matching

Not all relations that a knowledge model is trained with will be relevant to each extracted head. For example, a head entity, “*hammer*”, would ideally be matched to a relation such as `AtLocation`, while a relation such as `xWants` (*i.e.*, what does this head entity want) would not be matched. Similarly, “*PersonX becomes a basketball player*” might be matched to a relation such as `xIntent` (*i.e.*, what is the intent of the main persona in the head entity), while a relation such as `UsedFor` (*i.e.*, what is the head entity used for) would yield an incoherent inference. In this next stage, `kogito` matches relations to the given head input so that the resulting (*head, relation*) pair constitutes a sensible and plausible prompt for the knowledge model.

`kogito` supports relation matching as a pre-processing step before generating inferences. Suitable relation matches may be subjective depending on the use case, so `kogito` supports specifying subsets of relations and creation of custom relation matching modules developed by the user.⁹

In addition, `kogito` also provides native relation matching algorithms. These relation matchers follow the categorization of relations set out by Hwang et al. (2021), where relations were mapped into three categories: *Physical*, *Social* and *Event* types. Following this standard, we design relation matchers that identify a given head with whether it should be connected to the *Physical*, *Social* or *Event* categories, and match all relations in these categories to the head entity. Below, we describe three relation matching methods provided as part of `kogito`’s core library:

Base Matcher Every relation defined for a knowledge graph is matched to the head entities. This matcher is particularly useful if the user pre-defines a set of acceptable known relations or if they define new relations for their use case (§8).

Heuristic matcher The heuristic relation matcher matches extracted head entities that are noun phrases to *ATOMIC2020 Physical* relations and extracted head entities that are sentences or verb phrases to *Social* and *Event* relations. In our example, “*PersonX becomes a great basketball player*”, an extracted verb phrase such as “*become player*” would be matched to the *Social* and *Event* relations, while the extracted noun phrase

⁹<https://tinyurl.com/relation-matching>

Dataset	n_{train}	n_{test}	Overlap
Original	36,940	6,559	0.80 / 0.81
D_4	40,395	1,192	0.30 / 0.36
D_2	40,516	1,071	0.20 / 0.27
D_0	40,777	810	0.00 / 0.11

Table 1: Summary of Relation Matching datasets. The overlap column reports the degree of overlap with / without stopwords included.

"basketball player" would be matched to the *Physical* relations.

6.1 Model-based relation matching

The above matchers do not consider the semantic meaning of the head entities when matching them to relations. We also define model-based matchers that learn which heads and relations would be good matches. Relation matching is modeled as a classification problem. A head entity is given as input, and the model must determine the relation groups that match: *Physical*, *Social* and *Event*.

Dataset We use the ATOMIC2020 knowledge graph to train and evaluate the model-based relation matchers. First, we construct a dataset where the inputs are head entities and the label space corresponds to the three relation groups. If a head entity in the knowledge graph is connected to a relation from a particular group, we treat that relation group as a positive label for the head entity. As relations from multiple relation groups may be connected to a head entity, this labeling yields a multi-label prediction problem.

To evaluate the performance of our relation matchers (and test their generalization so they may be applicable to a broad scope of use cases), we split our dataset into both an in-distribution (ID) and an out-of-distribution (OOD) evaluation sample set. For the ID test set, we use the original ATOMIC2020 development set. For the OOD test set, we combine the train and test set of ATOMIC2020 and resplit this joint dataset while minimizing the word overlap between the train and test set. More specifically, we prepare 3 sets of (train, test) splits called D_0 , D_2 and D_4 where n in D_n is defined as the maximum number of times a word in a particular test set example can occur in the training dataset (excluding stopwords). A bigger n indicates more overlap between these two sets. In D_0 , the test set does not have any overlap-

Split	Head Entity	Labels
Train	PersonX acts funny	<i>event, social</i>
Train	accordion	<i>physical</i>
Train	big investment	<i>event</i>
Test	agenda	<i>physical</i>
Test	PersonX wreaks havoc	<i>event, social</i>
Test	PersonX motivates PersonY	<i>social</i>

Table 2: Samples from resplit train and test set D_0

ping non-stopwords with the training set. Finally, we ensure that the resulting test set is balanced over each relation group. Table 1 provides the summary of the constructed datasets and Table 2 lists some examples from the D_0 dataset.

Models We report results for fine-tuned models using different pretrained embeddings: GloVe (Pennington et al., 2014), BERT (Devlin et al., 2019) and DistilBERT (Sanh et al., 2019). The GloVe model uses the technique of Shen et al. (2018) with average pooling over 100 dimensional GloVe embeddings and a projection layer on top. The BERT and DistilBERT models are finetuned on the task with a projection layer to predict the label.¹⁰ These models are provided with `kogito`, and can be selected to match relations to head inputs.

In Table 3, we report the train, ID test and OOD test F1 scores for these models using different training datasets D_n , allowing users to understand their relative benefits and trade-offs.

7 Inference Filtering

By default, the commonsense inference module returns all generated tails without any filtering applied. However, many of these resulting inferences may be irrelevant to the initial context, particularly for extracted heads that have been decontextualized. Given most users may only be interested in relevant subsets of these commonsense inferences, `kogito` provides a separate module to determine the relevance of the given *knowledge tuples* with respect to the initial *context* from which it was extracted. In our running example, "PersonX becomes a great basketball player", an extracted head entity "player" may yield contextually-irrelevant inferences such as "player plays video games" and "player is at a soccer match", which

¹⁰All models are trained using binary cross-entropy loss and the Adam optimizer (Kingma and Ba, 2015) for 20 (for SWEM models) and 3 (for BERT and DistilBERT models) epochs with a batch size of 64.

Data	Model	Train F1	ID F1	OOD F1
D_4	Base	0.68	0.82	0.62
	Heuristic	0.84	0.80	0.69
	GloVe	0.90	0.91	0.82
	DistilBERT	0.97	0.91	0.85
	BERT	0.97	0.91	0.86
D_2	Base	0.68	0.82	0.61
	Heuristic	0.84	0.80	0.69
	GloVe	0.89	0.90	0.81
	DistilBERT	0.97	0.93	0.85
	BERT	0.97	0.94	0.86
D_0	Base	0.68	0.82	0.63
	Heuristic	0.84	0.80	0.73
	GloVe	0.89	0.90	0.76
	DistilBERT	0.97	0.93	0.84
	BERT	0.97	0.91	0.85

Table 3: Relation matcher performance on datasets D_n

would be filtered.

To filter inferences, `kogito` comes with the off-the-shelf DeBERTa-based commonsense fact linking model from Gao et al. (2022), which achieved a state-of-the-art average 72.5% F1 across multiple benchmarks. However, our setting is different from the one evaluated in Gao et al. (2022) as we evaluate generated commonsense inferences (rather than ones from an existing KB) for contextual relevance. To evaluate how well our method transfers to this new setting, we perform an expert study on the performance of the inference filtering model with respect to the knowledge generated from a knowledge model such as COMET. We randomly select 50 instances from the test split of ROC-ATOMIC dataset Gao et al. (2022) where each instance is composed of a *context* and a *fact* as a knowledge tuple (*head*, *relation*, *tail*). We then run the default `kogito` inference pipeline (with full head extraction and heuristic relation matching) on the *heads* which produces several inferences per head instance. We select 100 results randomly from the output of the previous step and apply our inference filtering model. Finally, we ask a human expert to annotate each instance with the true relevance label of the fact and find that our model achieves a 75% F1 on the knowledge model generated inferences. We also offer a modular interface to define and plug in new filtering models in the future.

8 Defining New Relations

In previous knowledge modeling papers (Bosselut et al., 2019; Hwang et al., 2021), the set of rela-

tions that can be used in prompts is limited by the knowledge graph used to train the knowledge model (e.g., ATOMIC2020). However, a user may want to generate inferences for new dimensions of knowledge, define their own custom relations for them, and produce commonsense inferences based on these new properties. However, if there are no large KGs that use this schema, training a suitable knowledge model would pose a challenge.

`kogito` provides this functionality by implementing the approach of West et al. (2022), which allows a user to prompt large language models for knowledge using custom relations and has been shown to generate high-quality knowledge. Specifically, a user defines an instance of a *knowledge relation* class, a verbalizer function that describes how to convert the new relation into a natural language prompt (with a head and tail), and an instruction prompt to GPT-3. At inference time, the user provides a list of sample knowledge tuples that use the new relation. These tuples are verbalized using the verbalizer function and provided to the GPT-3 model along with the instruction prompt. Below, we illustrate this process with an example where a new relation, `xWishes`, which describes person’s wishes, is defined using the sample code:

```
from kogito.core.relation import (KnowledgeRelation,
                                  register_relation)

def x_wishes_verbalizer(head, **kwargs):
    # index will be passed from the model
    # so that we can enumerate samples
    # which helps with inference
    index = kwargs.get("index")
    index_txt = f"{index}" if index is not None \
        else ""
    return f"Situation {index_txt}: {head}."
    "As a result, PersonX wishes"

X_WISHES = KnowledgeRelation("xWishes",
                              verbalizer=x_wishes_verbalizer,
                              prompt="How does this situation affect"
                                    " each character's wishes?")
register_relation(X_WISHES)
```

Then, to use this new relation for inference, the user can provide a sample knowledge graph (i.e., a prompt filled with example tuples using this relation), and a head such as "*PersonX makes a huge mistake*" to generate inferences about. Below, we show how such a sample knowledge graph could be verbalized into a prompt for GPT-3:

How does the situation affect the character's wishes?

Situation 1: John is at a party. As a result, John wishes to drink beer and dance

Situation 2: Terry bleeds a lot. As a result, Terry wishes to see a doctor

Situation 3: Eileen works as a cashier. As a result, Eileen wishes to be a store manager

Situation 4: James gets dirty. As a result, James wishes to clean up

Situation 5: Janice stays up all night studying. As a result, Janice wishes to sleep all day

Situation 6: Isaac makes a huge mistake. As a result, Isaac wishes...

The result of prompting GPT-3 with the above text is returned as the generated tail inference for the given head. Using this approach, users can instantiate a prompt defining a new relation, and use large language models to produce inferences for it.

9 Conclusion & Future Work

In this system description, we presented `kogito`, a toolkit for generating commonsense inferences for open-world text using knowledge models. `kogito` provides a foundational, customizable, and extensible interface for inference generation from knowledge models, and supports preprocessing and manipulation utilities such as head extraction, relation matching, and relation definition.

Future work may include improved head extraction, such as semantic head extraction (*e.g.*, paraphrased noun phrase extraction, etc.), new relation matching methods that more rigorously trade off performance and latency, support for new knowledge models trained on other knowledge graphs (*e.g.*, ANION; Jiang et al., 2021), and multimodal inputs such as images.

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Imaging, Sony Group Corporation, and the Allen Institute for AI.

Ethical Considerations

`kogito` is a library that uses knowledge models such as COMET (Bosselut et al., 2019) to generate commonsense inferences from text. These knowledge models are seeded with pretrained language models and subsequently finetuned on knowledge graphs so that they may generate knowledge in the structure of the finetuning KG. Consequently, `kogito` could reflect harmful behaviors exhibited by language models and knowledge graphs that are used to train the knowledge models in its library. For example, language models have been shown to encode biases about race, gender, and many other demographic attributes (Sheng et al., 2020; Weidinger et al., 2021). They can also generate toxic outputs when prompted in overt (Wallace et al., 2019), but also seemingly innocuous (Gehman et al., 2020), ways. We encourage users of this library to consider the same precautions they would apply to other language models and methods that use noisy knowledge sources.

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¹¹<https://github.com/allenai/comet-atomic-2020>

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