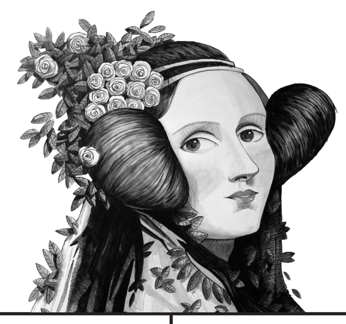
source{d}



technological stack for AI on code.

goo.gl/4bgBX2

similar repos search
motivation.

FIND, COMPARE & EXPLORE

‡ repositories that better fit needs
‡ new ideas, inspiration
‡ people with similar ideas
‡ compare libraries with the same purpose
‡ explore new areas of knowledge

how-to.

PREPARATION

‡ clone
‡ parse source code
‡ tokenization
‡ prepare Swivel input & TF-IDF
‡ train Swivel embeddings
‡ repo weighted nbow

SEARCH ALGO

Đ1 obama speaks to the media in illinois
1.07 = 0.45 +0.24 +0.20 +0.18
Đ0 the president greets the press in chicago
1.63 = 0.49 +0.42 +0.44 +0.28
Đ2 the band gave a concert in japan

Đ0 the president greets the press in chicago
1.30
Đ3 obama speaks in illinois

‡ centroid distance
‡ relaxed LP
(which gives a lower boundary)
‡ WMD only for best options

This allows to avoid 95% WMD evaluations

usage.

```
>>> import vecino
>>> engine = vecino.SimilarRepositories()
>>> root = "https://github.com/"
>>> repo = root + "tensorflow/tensorflow"
>>> print(engine.query(repo))
```

topic modeling
motivation.

WHY

‡ programmers use natural language in source code
‡ names are a rich source of information
‡ names help to understand project at high level
‡ names help to summarize content
‡ group projects that deal with the same topic

how-to.

PIPELINE

‡ repositories
‡ deduplicate repos (src-d/minhashcuda)
‡ select source code files only (src-d/enry)
‡ extract names (doc.bblf.sh)
‡ name processing (tokenization)
‡ filtering by DF
‡ bag-of-words per repository
‡ additive regularization of topic models (bigARTM)
‡ manual topic labeling

SHORT MATH

$$p(w|d) = \sum_{t \in T} p(w|t)p(t|d)$$

where w - term, d - document, t - topic

$$\sum_{d \in D}\sum_{w \in d} n_{dw} \ln \sum_{t} \phi_{wt}\theta_{td} + R(\Phi, \Theta) \to \max_{\Phi,\Theta}$$

the idea of ARTM - MLE + regularization R

$$R(\Phi, \Theta)_{Dirichlet} = \sum_{t,w}(\beta_w - 1)\ln \phi_{wt} + \sum_{d,t}(\alpha_t - 1)\ln \theta_{t,d}$$

LDA in terms of ARTM

usage.

```
# docker run srcd/github_topics apache/spark
```

‡ 18.52 spark
‡ 16.58 hadoop
‡ 13.86 java web servers
‡ 13.03 matplotlib; python machine learning
‡ 12.13 transport, gps

These numbers express the relative importance of a given topic for this repository

future
motivation.

WHY ML ON SOURCE CODE

‡ source code has strong patterns
‡ software is everywhere → tons of data
‡ complexity of source code is increasing
‡ transfer code patterns from best projects
‡ ~50M people who know how to program

ML APPLIED ON SOURCE CODE

‡ refactoring, suggestion, snippet search, ...
(coding assistance)
‡ automatic test generation, code review
‡ bug detection and fixing
‡ source code generation in narrow area
(like pixel2code)

SUGGESTIONS NOW

```
from django.db i
```

> if	if
> idea	idea
> im	import
> ifmain	if __name__ == '__main__':
> pdb	iPDB set trace

FUTURE SUGGESTIONS

```
from django.db
```

```
  import models
from django.utils.encoding import \
    python_2_unicode_compatible
>
@python_2_unicode_compatible
class test_from_model(models.Model):
    title = models.CharField(max_length=...)
```

tree-based nn.

MOTIVATION

‡ code has structure - AST
‡ AST differs from human lang structure
‡ AST contains rich information about code
‡ distance between items is shorter in tree
‡ AST will provide better context for items
‡ NN on tree will find great patterns in code

bblfsh.

USAGE

```
>>> python3 -m bblfsh -f source_file
```

MOTIVATION

‡ programming languages have AST
‡ leverage standard parser from each language
‡ normalize as a post-processing step: AST → UAST
‡ result: same UAST for different languages

HOW-TO

‡ lang drivers are packaged as docker containers
‡ server contains a lightweight container runtime
‡ no docker, no external runtime dependencies
‡ official drivers published at docker hub