Exploratory code search and snippet suggestion

Article review

Slavnov Konstantin
konstantin@sourced.tech

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Introduction

What is the **fastest** way to learn a new library?

New framework investigation ways:

- Documentation reading;
- Ask stackoverflow;
- Just start to use it;
- Search code examples;
- etc

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Insights from Searching and Skimming: An Exploratory Study [5].

Ways to solve

Let’s build a machine learning assistant!

Approaches:

- Topic modeling
- Hierarchical clustering
- Deep learning way
- Probabilistic way

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Topic modeling

Scheme

- Get a codebase of library usage
- Build a hierarchical topic modeling for codebase
- Show it for user API query
- ???
- PROFIT!

Flat topic model. Reminder

- Documents $d \in D$
- Tokens (words) $w \in W$
- Topics $t \in T$
- Document-token counters n_{dw}

Flat topic model:

$$P_{wd} = \frac{n_{dw}}{\sum_{w' \in W} n_{dw'}} = p(w \mid d) \approx \sum_{t \in T} p(w \mid t)\, p(t \mid d) = \sum_{tin} \phi_{wt} \theta_{td} = \{\Phi\Theta\}_{wd}$$

or just

$$P \approx \Phi\Theta$$

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Applying MLE:

$$L(\Psi, \Theta) = \sum_{d \in D} \sum_{w \in d} n_{dw} \ln \sum_{t} \psi_{wt} \theta_{td} \quad \longrightarrow \max_{\Psi, \Theta \text{ – stochastic}}$$

EM-algorithm is used for training.

Flat topic model.

BigARTM is good tool for it.

What we can do:

- Add regularisers:

$$L(\Psi, \Theta) + R(\Psi, \Theta) \longrightarrow \max$$

- Add modalities $m \in M$.

$$W = \bigsqcup_{m \in M} W_m \text{ and } \Phi = [\Phi_1 | \cdots | \Phi_n]$$

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Let's build **topic hierarchies**.

- Each level is a topic model.
- Next level is learned with **specific regulariser** to find parent topics from previous level.

Check out [6, 7].

Topic hierarchies.

- **Learned** parent level: topics $a \in A$ with $\Phi' \in \mathbb{R}^{|W| \times |A|}$ and $\Theta' \in \mathbb{R}^{|A| \times |D|}$.
- **To learn:**
  New level with topics $t \in T$ and $\Phi \in \mathbb{R}^{|W| \times |T|}$ and $\Theta \in \mathbb{R}^{|T| \times |D|}$.
  Parent-child relations Ψ_{ta} – t is a child of a.

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- **Assumption:** parent topic is a mixture of children's:

$$p(w \mid a) \approx \sum_{t \in T} p(w \mid t) p(t \mid a) \qquad \text{or just} \qquad \Phi^{l} \approx \Phi\Psi$$

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- We can just add $|A|$ pseudo documents with n_{wa} counters
- The same point with Θ regularisation. $\Theta^{l} \approx \tilde{\Psi}\Theta$ It is like add new modality with tokens corresponding to $a \in A$.

Hierarchy sparsing

The goal: Topics should have small number of parents.

$p(a \mid t)$ should be sparse.

Similar to LDA regulariser:

$$R(\Psi) = \frac{1}{|A|} \sum_{a} \sum_{t} \ln p(a \mid t) = \frac{1}{|A|} \sum_{a} \sum_{t} \ln \frac{\psi_{ta}\, p(a)}{\sum_{a'} \psi_{ta'}\, p(a')}$$

To apply we need just to update M-step of EM-algorithm.

The same approach for Θ regularisation.

Hierarchical clustering approach

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DocNADE

NADE – Neural Autoregressive Distribution Estimator [4].

Based on fact that $$p(v) = \prod_{d=1}^{D} p(v_d \mid v_{<d})$$

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$$h_d = \mathrm{sigm}(c + W_{:,<d}v_{<d}).$$

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source{d}

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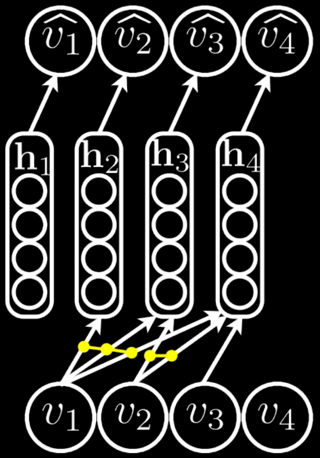
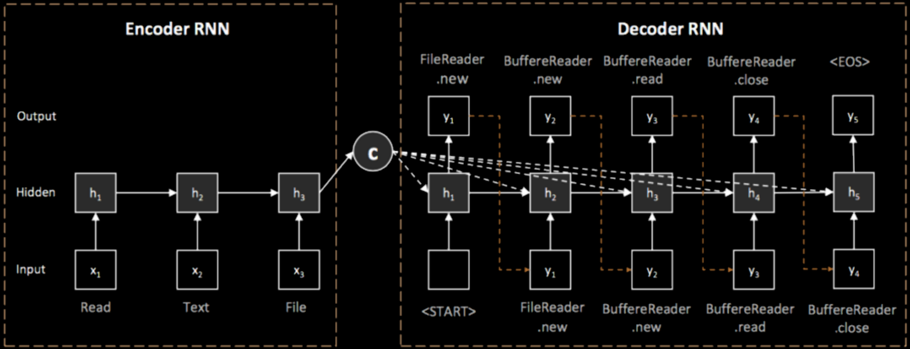
Trains on random permutations of the words in a document.

Document representation is h_T at the final timestep T.



Deep learning way

- **Aim:** Generate API sequences for a natural language query [3].
- **Method:** RNN encoder-decoder model for API learning.
- **Data:** annotated code snippets collected from GitHub.



source{d}

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Details:

- Run on sequences of API methods only.
- RNN is **GRU**, Encoder is bidirectional with attention, 1000 hidden units, 120 dimension of word embeddings.
- Beam Search for generation several API sequences to choose

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- Run on sequences of API methods only.
- RNN is **GRU**, Encoder is bidirectional with attention, 1000 hidden units, 120 dimension of word embeddings.
- Beam Search for generation several API sequences to choose
- IDF-based weights for API as a penalty term in **loss**:

$$\mathrm{loss}_{it} = -\log p_\theta(y_{it} \mid x_i) - \lambda \log\left(\frac{N}{n_t}\right)$$

where
i is i-th train instance,
t is t-th target word in instance i,
N is the total number of API sequences,
n_t is the number of sequences where the API t appears.

Probabilistic way. Interesting Sequence Mining

Task: get meaningful API patterns $\mathcal{I}$ [1, 2].

Idea: Use API patterns $\mathcal{I}$ to define a code probability in database X.

Pattern is interesting code **subsequence**.

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Simplified model:

$$p(X, z \mid \mathcal{I}) \sim \prod_{i \in \mathcal{I} \cap X} p_i^{z_i} (1 - p_i)^{1 - z_i}$$

X – code database,
$\mathcal{I}$ – set of API patterns,
p_i – API pattern $i \in \mathcal{I}$ probability,
z_i – indicator of including pattern into code (hidden).

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Example:

$$X = \{\ d\ b\ c\ e\ d\ f\ f;\ \ e\ e\ d\ f\ f\ f;\ \ d\ f\ d\ e\ f\ f;\ \}$$

$$\mathcal{I} = \{\ [\,b\ c\ e\,]\ [\,d\ f\,]\ [\,d\ f\,]\ [\,e\ f\,]\ \}$$

	[b c e]	[d f]	[d f]	[e f]
	1	1	1	0
z :	0	1	0	1
	0	1	1	1
p_i :	0.33	1	0.66	0.66

Probabilistic way. Interesting Sequence Mining

Solver: EM-algorithm.

Iterate:

1. Structural-EM ($\mathcal{I}$ update)
   1.1 Somehow generate candidate S'
   1.2 See if quality increases
2. Hard-EM (z and p update)
   2.1 Find patterns from $\mathcal{I}$ that was used to sample X with greedy search.

$$z = \arg\max_z \log p(z \mid p, \mathcal{I}; X)$$

   2.2 Update p_i by averaging z.

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References. Links

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2. BigARTM for Topic Modeling
3. Post about DocNADE with implementation
4. Probabilistic API Mining code

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