Faster methods for software analytics!

Wei Fu

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Find these slides at: http://tiny.cc/wfuExam17

Sep, 2017
software analytics
software analytics

To enable software practitioners to perform data exploration and analysis in order to obtain insightful and actionable information for data-driven tasks around software.
To enable software practitioners to perform data exploration and analysis in order to obtain insightful and actionable information for data-driven tasks around software.
软件分析

为了使软件实践者能够进行数据探索和分析，以便获得数据驱动任务周围软件的洞察和可操作信息。
Defect prediction  Linkable questions prediction

software analytics
Defect prediction Linkable questions prediction software analytics
Defect prediction

Linkable questions prediction

software analytics
Defect prediction  Linkable questions prediction

software analytics
Defect prediction

Linkable questions prediction

TUNING!

software analytics
• Is tuning with DE helpful?

• Is tuning with DE a faster method?

• How to improve tuning with DE?
● **Is tuning with DE **helpful**?**
  ○ Tuning for defect predictors (**IST’16**)
  ○ Tuning for topic modeling (**IST**, minor revision)

● **Is tuning with DE a **faster** method?**

● **How to **improve** tuning with DE?**
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● **How to improve tuning with DE?**
  ○ Future work...
Tuning for every task

Knowledge reuse

Tuning should be faster

Simple method first
Faster methods for software analytics!
Why Faster Software Analytics?

- **CPU**
- **Cost (cloud service)**
- **Reproducibility**

- Arcuri et al.\(^{[\text{Arcuri2011}]}\) reported their tuning requires *weeks, or more* of CPU time.

- Wang et al.\(^{[\text{Wang2013}]}\) require *weeks to years* to learn control settings.

- Deep learning:
  - Lam et al.\(^{[\text{Lam2015}]}\): *weeks* of CPU.
  - Gu et al.\(^{[\text{Gu2016}]}\): *240 hours* of GPU.
Why Faster Software Analytics?

- CPU
- Cost (cloud service)
- Reproducibility

AWS cost:  Computing + Bandwidth + Storage +...
Why Faster Software Analytics?

- CPU
- Cost (cloud service)
- Reproducibility

Wang et al. [Wang 2013] 15 years of CPU time to do code clone detection
TUNING (with DE)!
Tuning is **Ignored** in SE!

Tuning is **Ignored** in SE!


- Never Mention Tuning: 78%
- Just Mention Tuning: 14%
- Manually Tuning: 4%
- Grid Search*: 2%
- DE: 2%

out of 52 highly cited defect prediction papers
Why Tuning Ignored?

Cause they are so well explored all already... right?

CPU intensive!
● Is tuning with DE helpful?
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● How to improve tuning with DE?
  ○ Future work...
Easy over Hard: A Case Study on Deep Learning

Wei Fu, Tim Menzies
Com.Sci., NC State, USA
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ABSTRACT
While deep learning is an exciting new technique, the benefits of this method need to be assessed with respect to its computational cost. This is particularly important for deep learning since these learners need hours (to weeks) to train the model. Such long training time limits the ability of (a) a researcher to test the stability of their conclusion via repeated runs with different random seeds; and (b) other researchers to repeat, improve, or even refute that original work.

For example, recently, deep learning was used to find which questions in the Stack Overflow programmer discussion forum can be linked together. That deep learning system took 14 hours to execute. We show here that applying a very simple optimizer called DE to fine tune SVM, it can achieve similar (and sometimes better) semantically related, they are considered as linkable knowledge units.

In their paper, they used a convolution neural network (CNN), a kind of deep learning method [42], to predict whether two KUs are linkable. Such CNNs are highly computationally expensive, often requiring network composed of 10 to 20 layers, hundreds of millions of weights and billions of connections between units [42]. Even with advanced hardware and algorithm parallelization, training deep learning models still requires hours to weeks. For example:

- XU report that their analysis required 14 hours of CPU.
- Le [40] used a cluster with 1,000 machines (16,000 cores) for three days to train a deep learner.

This paper debates what methods should be recommended to those wishing to repeat the analysis of XU. We focus on whether

$\text{DE + SVM} \checkmark \quad \text{Deep learning} \times$
# Deep Learning in SE

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# Deep Learning in SE

## Trade-off: Benefit vs. Cost?

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Method
Case Study

Linkable Questions Prediction on StackOverflow
Predicting Semantically Linkable Knowledge in Developer Online Forums via Convolutional Neural Network

Bowen Xu\textsuperscript{1}, Deheng Ye\textsuperscript{2}, Zhenchang Xing\textsuperscript{3}, Xin Xia\textsuperscript{1}, Guibin Chen\textsuperscript{1}, Shanping Li\textsuperscript{3}
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\textsuperscript{2}School of Computer Science and Engineering, Nanyang Technological University, Singapore
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xxia@zju.edu.cn, gbchen@ntu.edu.sg, shan@zju.edu.cn

ABSTRACT
Consider a question and its answers in Stack Overflow as a knowledge unit. Knowledge units often contain semantically relevant knowledge, and thus linkable for different purposes, such as duplicate questions, directly linkable for problem solving, indirectly linkable for related information. Recognising different classes of linkable knowledge would support more targeted information needs when users search or explore the knowledge base. Existing methods focus on binary relatedness (i.e., related or not), and are not robust to recognize different classes of semantic relatedness when linkable knowledge units share few words in common (i.e., have lexical gap). In this paper, we formulate the problem of predicting semantically linkable knowledge units as a multiclass classification problem, and solve the problem using deep learning techniques. To overcome the lexical gap issue, we adopt neural language model (word embeddings) and convolutional neural network (CNN) to capture word- and document-level semantics of knowledge units. Instead of using human-engineered classifier features which are hard to design for informal user-generated content, we exploit large amounts of different types of user-created knowledge-unit links to train the CNN to learn the most informative word-level and document-level features for the multiclass classification task. Our evaluation shows that our deep-learning based approach significantly and consistently outperforms traditional methods using traditional word representations and human-engineered classifier features.

Keywords
Link prediction, Semantic relatedness, Multiclass classification, Deep learning, Mining software repositories

1. INTRODUCTION
In Stack Overflow, computer programming knowledge has been shared through millions of questions and answers. We consider a Stack Overflow question with its entire set of answers as a knowledge unit regarding some programming-specific issues. The knowledge contained in one unit is likely to be related to knowledge in other units. When asking a question or providing an answer in Stack Overflow, users reference existing questions and answers that contain relevant knowledge by URL sharing [46], which is strongly encouraged by Stack Overflow [2]. Through URL sharing, a network of linkable knowledge units has been formed over time [46].

Unlike linked pages on Wikipedia that follows the underlying knowledge structure, questions and answers are specific to individual’s programming issues, and URL sharing in Q&A is opportunistic, because it is based on the community awareness of the presence of relevant questions and answers. A recent study by Ye et al. [46] shows that the structure of the knowledge network that URL sharing activities create is scale free. A scale-free network follows a power law degree distribution, which can be explained using preferential attachment theory [4], i.e., “the rich get richer”. On
Predictor

Duplicate

Direct Link

Indirect Link

Isolated
Question A

Question B

Predictor

Duplicate

Direct Link

Indirect Link

Isolated
Learners

- **Baseline:**
  - SVM

- **Xu’s deep learning method:**
  - CNN (convolutional neural networks)

- **Our proposed method:**
  - SVM + DE

Parameters in SVM (scikit-learn):
- C, kernel, gamma, coef0
Tuning Algorithm: Differential Evolution*

Population = Pick N options at random # e.g. N = 10

M times repeat : # e.g. M = 5

for Parent in Population:

- Select a, b, c = three other items in population.
- Candidate = a + f*(b-c) # ish
- if Candidate “better”, replace Parent.

Experimental Setup

Train Word2Vec
- 100,000 KU texts
- Train
- Word2Vec

Parameter Tuning
- DE
- Parameters
- Train
- Evaluate
- SVM

Training KU pairs
- Lookup
- Train Learner

New Training KU vectors
- Train
- Tuning KU vectors
- SVM
- Best Tunings

Testing KU pairs
- Lookup
- Test Learner

Testing KU vectors
- Predict
- Results
Experimental Setup
Experimental Setup

100,000 KU texts
Train
Word2Vec

Train Word2Vec

DE
Parameters
Train
Evaluate
SVM

New Training KU vectors

Tuning KU vectors

Testing KU pairs
Lookup

Training KU pairs
Lookup

Train Learner

Test Learner

Testing KU vectors

Predict
Results

NC STATE UNIVERSITY
Experimental Setup

- **Train Word2Vec**
  - 100,000 KU texts
  - Train
  - Word2Vec

- **Parameter Tuning**
  - DE
  - Parameters
  - Train
  - Evaluate
  - SVM

- **Training KU pairs**
  - Lookup
  - Train
  - Word Embeddings
  - New Training KU vectors
  - Tuning KU vectors
  - SVM
  - Train
  - Best Tunings

- **Testing KU pairs**
  - Lookup
  - Testing KU vectors
  - Predict
  - Results
Experimental Setup

1. Train Word2Vec with 100,000 KU texts.
2. Parameter Tuning using SVM.
3. Training KU pairs lookup.
4. Test Learner with Testing KU pairs.
5. Predict Testing KU vectors to get Results.
Results
Research Questions

RQ1: Can we reproduce Xu’s baseline results?

RQ2: DE+SVM outperforms Xu’s deep learning method?

RQ3: DE+SVM faster than Xu’s deep learning method?
RQ1: Reproduce Xu’s Baseline Results?

Comparison of our baseline method with Xu’s baseline. Best scores are marked in bold.

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Score Delta(F1) = Our SVM - Xu’s SVM = -0.06
RQ1: Reproduce Xu’s Baseline Results?
RQ1: Reproduce Xu’s Baseline Results?

Overall, we got similar results to the baseline method reported in Xu’s study.
Research Questions

RQ1: Can we reproduce Xu’s baseline results?

RQ2: DE+SVM outperforms Xu’s deep learning method?

RQ3: DE+SVM faster than Xu’s deep learning method?
RQ2: DE+SVM Outperforms Xu’s CNN?
RQ2: DE+SVM Outperforms Xu’s CNN?

Deep learning (CNN) does not have any performance advantage over DE+SVM.
Research Questions

RQ1: Can we reproduce Xu’s baseline results?

RQ2: DE+SVM outperforms Xu’s deep learning method?

RQ3: DE+SVM faster than Xu’s deep learning method?
RQ3: Faster than Xu’s CNN?

DE+SVM is 84X faster than deep learning (CNN) in terms of model building.
Conclusion
Observation

For this case study:

Simple DE tuning performs *Better & Faster* than deep learning!
Another FSE’17 Paper on Deep Learning

Are Deep Neural Networks the Best Choice for Modeling Source Code?

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ABSTRACT

Current statistical language modeling techniques, including deep-learning based models, have proven to be quite effective for source code. We argue here that the special properties of source code can be exploited for further improvements. In this work, we enhance established language modeling approaches to handle the special challenges of modeling source code, such as: frequent changes, larger, changing vocabularies, deeply nested scopes, etc. We present a fast, nested language modeling toolkit specifically designed for software, with the ability to add & remove text, and mix & swap out many models. Specifically, we improve upon prior cache-modeling work and present a model with a much more expansive, multi-level notion of locality that we show to be well-suited for modeling software. We present results on varying corpora in comparison with traditional N-gram, as well as RNN, and LSTM deep-learning language models, and release all our source code for public use.

Our evaluations suggest that carefully adapting N-gram models for source code can yield performance that surpasses even RNN and LSTM based deep-learning models.

Statistical models from NLP, estimated over the large volumes of code available in GitHub, have led to a wide range of applications in software engineering. High-performance language models are widely used to improve performance on NLP-related tasks, such as translation, speech-recognition, and query completion; similarly, better language models for source code are known to improve performance in tasks such as code completion [15]. Developing models that can address (and exploit) the special properties of source code is central to this enterprise.

Language models for NLP have been developed over decades, and are highly refined; however, many of the design decisions baked into modern NLP language models are finely-wrought to exploit properties of natural language corpora. These properties aren’t always relevant to source code, so that adapting NLP models to the special features of source code can be helpful. We discuss 3 important issues and their modeling implications in detail below.

Unlimited Vocabulary Code and NL can both have an unbounded vocabulary; however, in NL corpora, the vocabulary usually saturates quickly: when scanning through a large NL corpus, pretty
Implication

For future deep learning in SE:

- **TUNE** your baseline methods.
- Do not ignore the **COST** of deep learning.
• *Is tuning with DE helpful?*
  ○ Tuning for defect predictors (*IST*’16)
  ○ Tuning for topic modeling (*IST*, minor revision)

• *Is tuning with DE a faster method?*
  ○ DE v.s. grid search (under review)
  ○ DE+SVM v.s. deep learning (*FSE*’17)

• *How to improve tuning with DE?*
  ○ *Future work...*
10 minutes tuning is **NOT TRUE** for all SE tasks!

That depends on:

- Learners (SVM, random forests, deep learning,...)
- Software analytic tasks (data, goal,....)
- Searching algorithms (DE, GA,....)
Challenge

Given a **limited budget**, can we **improve** performance of tuning?
Recap on Tuning with DE

Objective
(e.g, F1)

Better

Randomly Initialize N points as parents (N=5)

Objective space, points represent scores of tunings (parameters),
e.g. F1 score of (C=1.2, gamma=0.5, coff=1)= 0.3

Tunings sorted

(C=2.2, gamma=0.3, coff=2)

(C=1.8, gamma=0.9, coff=0.2)
Recap on Tuning with DE

Objective (e.g., F1)

Better

Randomly Initialize N points as parents (N=5)

Position 0

Tunings sorted

Objective space, points represent scores of tunings (parameters), e.g. F1 score of \((C=1.2, \gamma=0.5, \text{coff}=1)\) = 0.3
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Recap on Tuning with DE

Objective space, points represent scores of tunings (parameters).

Objective (e.g., F1)

Better

Tuning stopped given a limited budget
Recap on Tuning with DE

Objective space, points represent scores of tunings (parameters).

Objective (e.g., F1)

Better

Tuning stopped given a limited budget

Push these points further to the optimal direction?

Objective space, points represent scores of tunings (parameters).
Recap on Tuning with DE

Objective space, points represent scores of tunings (parameters).

Tuning stopped given a limited budget

Can we push them here?

Better
Tuning with DE: Better Initialization?

Objective (e.g., F1)

Objective space, points represent scores of tunings (parameters).

Initialize these points as parents? Tuning start here?

Better
Tuning with DE: Get Better Results?

Objective (e.g., F1)

Tunings sorted

Objective space, points represent scores of tunings (parameters).

Tuning stopped given a limited budget

We expect tuning to stop here
Tuning with DE: Get Even Better?

Objective (e.g., F1)

Tuning stopped given a limited budget

Even better?!

Objective space, points represent scores of tunings (parameters).
We Need a Better Initialization!

Objective space, points represent scores of tunings (parameters).

Randomly Initialize N points as parents (N=5)

Objective (e.g., F1)

Improved

Better

Tunings sorted
We Got Some Experience...

Heterogeneous Defect Prediction

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Abstract—Many recent studies have documented the success of cross-project defect prediction (CPDP) to predict defects for new projects lacking in defect data by using prediction models built by other projects. However, most studies share the same limitations: it requires homogeneous data, i.e., different projects must describe themselves using the same metrics. This paper presents methods for heterogeneous defect prediction (HDP) that matches up different metrics in different projects. Metric matching for HDP requires a “large enough” sample of distributions in the source and target projects—this raises the question on how large is “large enough” for effective heterogeneous defect prediction. This paper shows that empirically and theoretically, “large enough” may be very small indeed. For example, using a mathematical model of defect prediction, we identify categories of data sets as few as 50 instances are enough to build a defect prediction model. Our conclusion for this work is that, even when projects use different metric sets, it is possible to quickly transfer lessons learned about defect prediction.

Index Terms—defect prediction, quality assurance, heterogeneous metrics, transfer learning.

TSE 2017
Other Researchers Reported...


Transfer Learning for Improving Model Predictions in Highly Configurable Software
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ICPE 2017

Transferring Performance Prediction Models Across Different Hardware Platforms
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Our Proposed Idea

Transfer Learning

Parameter Tuning

Transfer Tuning
Differential Evolution:

Population = Pick N options at random # e.g. N = 10

M times repeat : # e.g. M = 5

for Parent in Frontier:

- Select a, b, c = three other frontier items.
- Candidate = a + f*(b-c) # ish
- if Candidate “better”, replace Parent.
Another Illustration

Present:

1. Population = Pick N options at random # e.g. N =10
2. Population = Pick N options at random # e.g. N =10
3. Population = Pick N options at random # e.g. N =10
4. Population = Pick N options at random # e.g. N =10
Another Illustration

Future:

Population = Pick N options \# e.g. N =10

\[ \ldots \]

Transfer Knowledge
Preliminary Results - Defect Prediction

Learner: CART, Performance metric: Precision

CamelV0

- No transfer ==> 0.521
- Transfer from log4j ==> 0.667
- Transfer from luence ==> 0.667

CamelV1

- No transfer ==> 0.398
- Transfer from jeditV2 ==> 0.8
- Transfer from log4j ==> 0.8
- Transfer from poiV1 ==> 0.8
Preliminary Results - Defect Prediction

Learner: CART, Performance metric: F1

XercesV1
- No Transfer ==> 0.399
- Transfer from poiV1 ==> 0.56
- Transfer from synapse ==> 0.488

PoiV0
- No Transfer ==> 0.728
- Transfer from antV2 ==> 0.804
- Transfer from synapse ==> 0.819
Challenges

• Better transfer learning strategy for transfer tuning.
• Understand why and when transfer learning works for tuning.
• How to generalize to other software analytics?
My progress so far....

Parameter Tuning

- Apr, 16 Tuning (IST 2016)
- Dec, 16 DE better? (Under Review)
- Jan, 17 DE + LDA¹ (IST Minor Revision)
- Jun, 17 Easy over Hard (FSE'17)

Transfer Learning

- Failed Experiments
- HDP² (TSE 17) June, 17

1. This is a joint work with Amrit Agrawal
2. This is a joint work with Dr. JC Nam from Waterloo University.
Plan of work

Parameter Tuning

- April 16, Tuning (IST 2016)
- December 16, DE better? (Under Review)
- January 17, DE + LDA\(^1\) (IST Minor Revision)
- September 17, Easy over Hard (FSE 2017)

Transfer Learning

- June 17, Failed Experiments
- September 17, HDP\(^2\) (TSE 2017)
- June 17, Transfer tuning (Dec 2017?)

1. This is a joint work with Amrit Agrawal
2. This is a joint work with Dr. JC Nam from Waterloo University.
Q & A

- **Is tuning with DE helpful?**
  - Tuning for defect predictors (**IST’16**)
  - Tuning for topic modeling (**IST**, minor revision)

- **Is tuning with DE a faster method?**
  - DE v.s. grid search (under review)
  - DE+SVM v.s. deep learning (**FSE’17**)

- **How to improve tuning with DE?**
  - Future work...
Reference


