How much data is enough?
Predicting accuracy on large datasets from smaller pilot data

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Outline

Introduction

Empirical models of accuracy vs training data size

Accuracy extrapolation task

Conclusions and future work
ML as an engineering discipline

• A mature engineering discipline should be able to predict the cost of a project before it starts.
• Collecting/producing training data is typically the most expensive part of an ML or NLP project.
• We usually have only the vaguest idea of how accuracy is related to training data size and quality.
  ▶ More data produces better accuracy.
  ▶ Higher quality data (closer domain, less noise) produces better accuracy.
  ▶ But we usually have no idea how much data or what quality of data is required to achieve a given performance goal.
• Imagine if engineers designed bridges the way we build systems!

See statistical power analysis for experimental design, e.g., Cohen (1992).
Goals of this research project

• Given desiderata (accuracy, speed, computational and data resource pricing, etc.) for an ML/NLP system, design for a system that meets these.
• Example: design a semantic parser for a target application domain that achieves 95% accuracy across a given range of queries.
  ▶ What hardware/software should I use?
  ▶ How many labelled training examples do I need?
• Idea: Extrapolate performance from small pilot data to predict performance on much larger data
What this paper contributes

• Studies different methods for predicting accuracy on a full dataset from results on a small pilot dataset
• We propose new accuracy extrapolation task, provide results for the 9 extrapolation methods on 8 text corpora
  ▶ Uses the fastText document classifier and corpora (Joulin et al., 2016)
• Investigates three extrapolation models and three item weighting functions for predicting accuracy as a function of training data size
  ▶ Easily inverted to estimate training size required to achieve a target accuracy
• Highlights the importance of hyperparameter tuning and item weighting in extrapolation
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Overview

- **Extrapolation models** of how error $e (= 1 - accuracy)$ depends on training data size $n$
  - **Power law**: $\hat{e}(n) = bn^c$
  - **Inverse square-root**: $\hat{e}(n) = a + bn^{-1/2}$
  - **Biased power law**: $\hat{e}(n) = a + bn^c$
- Extrapolation model estimated from multiple runs using *weighted least squares regression*
  - Model trained on *different-sized subsets of pilot data*
  - Same test set is used to evaluate each run
  - The evaluation of each model training/test run is a training data point for extrapolation model
- **Weighting functions** for least squares regression
  - **constant weight** $(1)$
  - **linear weight** $(n)$
  - **binomial weight** $(n/e(1 - e))$

See e.g., Haussler et al. (1996); Mukherjee et al. (2003); Figueroa et al. (2012); Beleites et al. (2013); Hajian-Tilaki (2014); Cho et al. (2015); Sun et al. (2017); Barone et al. (2017); Hestness et al. (2017)
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| Corpus                  | Labels | Train (K) | Test (K) |
|-------------------------|--------|-----------|----------|
| Development             |        |           |          |
| ag_news                 | 4      | 120       | 7.6      |
| dbpedia                 | 14     | 560       | 70       |
| amazon_review_full      | 5      | 3,000     | 650      |
| yelp_review_polarity    | 2      | 560       | 38       |
| Evaluation              |        |           |          |
| amazon_review_polarity  | 2      | 3,600     | 400      |
| sogou_news              | 5      | 450       | 60       |
| yahoo_answers           | 10     | 1,400     | 60       |
| yelp_review_full        | 5      | 650       | 50       |

- FastText document classifier & data
  - 4 development corpora
  - 4 evaluation corpora
  - Joulin et al. (2016)’s train/test division
- Pilot data is 0.5 or 0.1 of train data
- Goal: *use pilot data to predict test accuracy when trained on full train data*
Extrapolation on ag_news corpus

- Extrapolation with biased power-law model \((\hat{e}(n) = a + bn^c)\) and binomial weights \((n/e(1 - e))\)
- Extrapolation from 0.5 training data is generally good
- Extrapolation from 0.1 training data is poor unless hyperparameters are optimised at each subset of pilot data
Relative residuals \((\hat{e}/e - 1)\) on dev corpora
RMS relative residuals on test corpora

| Pilot data | amazon review polarity | sogou news | yahoo answers | yelp review full | Overall |
|------------|------------------------|-----------|---------------|-----------------|---------|
| = 0.1      | 0.1016                 | 0.2752    | 0.0519        | 0.0496          | 0.1510  |
| ≤ 0.1      | 0.0209                 | 0.1900    | 0.0264        | 0.0406          | 0.0986  |
| = 0.5      | 0.0338                 | 0.0438    | 0.0254        | 0.0160          | 0.0315  |
| ≤ 0.5      | 0.0049                 | 0.0390    | 0.0053        | 0.0046          | 0.0200  |

- Based on dev corpora results, use:
  - biased power law model \((\hat{e}(n) = a + bn^c)\)
  - binomial item weights \((n/e(1-e))\)
- Evaluate extrapolations with RMS of relative residuals \((\hat{e}/e - 1)\)
- Larger pilot data \(\Rightarrow\) smaller extrapolation error
- Optimise hyperparameters at each pilot subset \(\Rightarrow\) smaller extrapolation error
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- The field need methods for predicting how much training data a system needs to achieve a target performance
- We introduced an *extrapolation task* for predicting a classifier’s accuracy on a large dataset from a small pilot dataset
- Highlight the importance of *hyperparameter tuning* and *item weighting*
- Future work: *extrapolation methods that don’t require expensive hyperparameter optimisation*
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