Feature selection

LING 572 Advanced Statistical Methods for NLP
January 21, 2020

Announcements

- HW1: avg 91.2, good job! Two recurring patterns:
  - Q2c: not using second derivatives to show *global* optimum
  - Q4b: HMM trigram tagger states
    - T^2, not T: states correspond to previous two tags'
- Thanks for using Canvas discussions!
- HW3 is out today (more later): implement Naïve Bayes
- Reading assignment 1 also out: due **11AM** on Tues, Jan 28

kNN at the cutting edge

Generalization through Memorization: Nearest Neighbor Language Models

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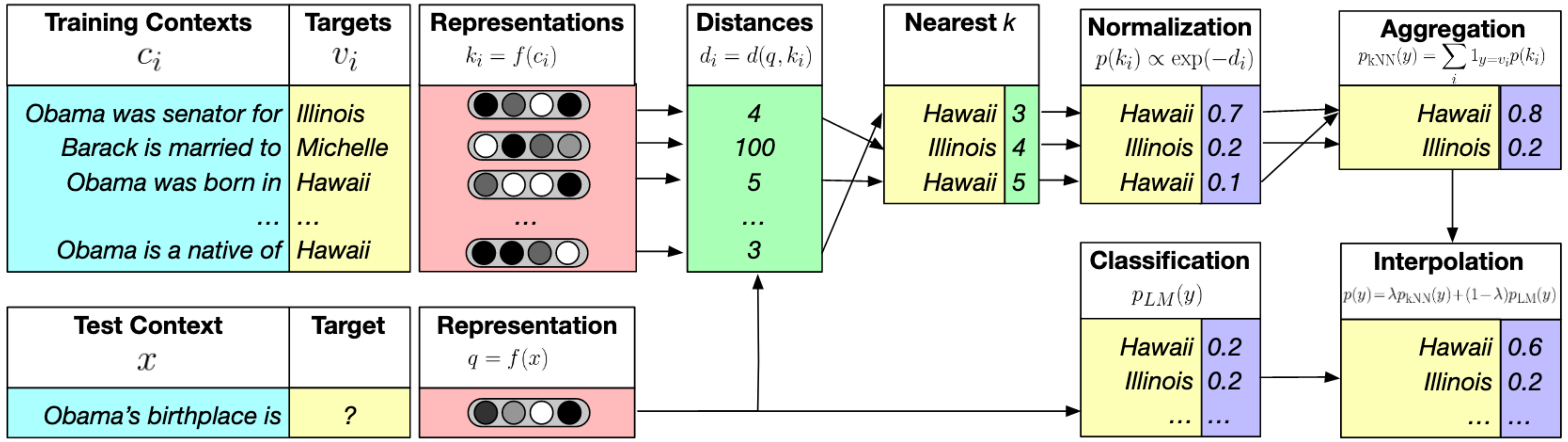
Abstract

We introduce kNN-LMs, which extend a pre-trained neural language model (LM) by linearly interpolating it with a k-nearest neighbors (kNN) model. The nearest neighbors are computed according to distance in the pre-trained LM embedding space, and can be drawn from any text collection, including the original LM training data. Applying this augmentation to a strong Wikitext-103 LM, with neighbors drawn from the original training set, our kNN-LM achieves a new state-of-the-art perplexity of 15.79 – a 2.9 point improvement with no additional training. We also show that this approach has implications for efficiently scaling up to larger training sets and allows for effective domain adaptation, by simply varying the nearest neighbor datastore, again without further training. Qualitatively, the model is particularly helpful in predicting rare patterns, such as factual knowledge. Together, these results strongly suggest that learning similarity between sequences of text is easier than predicting the next word, and that nearest neighbor search is an effective approach for language modeling in the long tail.

kNN at the cutting edge



Model	Perplexity (↓) Dev	Test	# Trainable Params
Baevski & Auli (2019)	17.96	18.65	247M
+Transformer-XL (Dai et al., 2019)	-	18.30	257M
+Phrase Induction (Luo et al., 2019)	-	17.40	257M
Base LM (Baevski & Auli, 2019)	17.96	18.65	247M
+kNN-LM	**16.06**	**16.12**	247M
+Continuous Cache (Grave et al., 2017c)	17.67	18.27	247M
+kNN-LM + Continuous Cache	**15.81**	**15.79**	247M

Outline

- Curse of Dimentionsality
- Dimensionality reduction
- Some scoring functions **
- Chi-square score and Chi-square test

In this lecture, we will use “term” and “feature” interchangeably.

Create attribute-value table

	f_1	f_2	…	f_K	y
x_1					
x_2					
…					

- Choose features:
  - Define feature templates
  - Instantiate the feature templates
  - Dimensionality reduction: feature selection

- Feature weighting
  - Global feature weighting: weight the whole column
  - Class-based feature weighting: weights depend on y

Feature Selection Example

- Task: Text classification
- Feature template definition:
  - Word – just one template
- Feature instantiation:
  - Words from training data
- Feature selection:
  - Stopword removal: remove top K (~100) highest freq
    - Words like: the, a, have, is, to, for,…
- Feature weighting:
  - Apply tf*idf feature weighting
    - tf = term frequency; idf = inverse document frequency

The Curse of Dimensionality

- Think of the instances as vectors of features
  - # of features = # of dimensions

- Number of features potentially enormous
  - e.g., # words in corpus continues to increase w/corpus size

- High dimensionality problematic:
  - Leads to difficulty with estimation/learning
    - Hard to create valid model
    - Hard to predict and generalize – think kNN
    - More dimensions → more samples needed to learn model

  - Leads to high computational cost

Breaking the Curse

- Dimensionality reduction:
  - Produce a representation with fewer dimensions
    - But with comparable performance

  - More formally, given an original feature set r
    - Create a new set r'(with $|r'| < |r|$), with comparable performance

Outline

- Dimensionality reduction
- Some scoring functions **
- Chi-square score and Chi-square test

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Dimensionality reduction (DR)

Dimensionality reduction (DR)

- What is DR?
  - Given a feature set r, create a new set r', s.t.
    - r' is much smaller than r, and
    - the classification performance does not suffer too much.

- Why DR?
  - ML algorithms do not scale well.
  - DR can reduce overfitting.

Dimensionality Reduction

- Given an initial feature set r,
  - Create a feature set r' such that |r'| < |r|

- Approaches:
  - r': same for all classes (a.k.a. global), vs
  - r': different for each class (a.k.a. local)

  - Feature selection/filtering
  - Feature mapping (a.k.a. extraction)

Feature Selection

- Feature selection:
  - r’ is a subset of r

- How can we pick features?

- Extrinsic ‘wrapper’ approaches:
  - For each subset of features:
    - Build, evaluate classifier for some task
  - Pick subset of features with best performance

- Intrinsic ‘filtering’ methods:
  - Use some intrinsic (statistical?) measure
  - Pick features with highest scores

Feature Selection

- Wrapper approach:
  - Pros:
    - Easy to understand, implement
    - Clear relationship between selected features and task performance.
  - Cons:
    - Computationally intractable: $2^{|r|} \cdot (\text{train} + \text{test})$
    - Specific to task, classifier
- Filtering approach:
  - Pros: theoretical basis, less task+classifier specific
  - Cons: Doesn't always boost task performance

Feature selection by filtering

- Main idea: rank features according to predetermined numerical functions that measure the “importance” of the terms.
- Fast and classifier-independent.
- Scoring functions:
  - Information Gain
  - Mutual information
  - chi square (χ^2)
  - …

Feature Mapping

- Feature mapping (extraction) approaches
  - r' represents combinations/transformations of features in r
    - Ex: many words near-synonyms, but treated as unrelated
    - Map to new concept representing all
      - big, large, huge, gigantic, enormous → concept of 'bigness'

- Examples:
  - Term classes: e.g. class-based n-grams
    - Derived from term clusters
  - Latent Semantic Analysis (LSA/LSI), PCA
    - Result of Singular Value Decomposition (SVD) on matrix produces 'closest' rank r' approximation of original

Feature Mapping

- Pros:
  - Data-driven
  - Theoretical basis – guarantees on matrix similarity
  - Not bound by initial feature space

- Cons:
  - Some ad-hoc factors:
    - e.g., # of dimensions
  - Resulting feature space can be hard to interpret

Quick summary so far

- DR: to reduce the number of features
  - Local DR vs. global DR
  - Feature extraction vs. feature selection

- Feature extraction:
  - Feature clustering
  - Latent semantic indexing (LSI)

- Feature selection:
  - Wrapping method
  - Filtering method: different functions

Feature scoring measures

Basic Notation, Distributions

- Assume binary representation of terms, classes
- t_k: term in T; c_i: class in C
- $P(t_k)$: proportion of documents in which t_k appears
- $P(c_i)$: proportion of documents of class c_i
  - Binary so we also have
    - $P(\overline{t_k}), P(\overline{c_i}), P(t_k, c_i), P(\overline{t_k}, c_i), \ldots$

Calculating basic distributions

	$\overline{c_i}$	c_i
$\overline{t_k}$	a	b
t_k	c	d

$$P(t_k, c_i) = \frac{d}{N}$$

$$P(t_k) = \frac{c+d}{N}$$

$$P(c_i) = \frac{b+d}{N}$$

$$P(t_k \mid c_i) = \frac{d}{b+d}$$

where $N = a + b + c + d$

Feature selection functions

- Question: What makes a good feature?

- Intuition: for c_i, the most valuable features are those that are distributed most differently among the positive and negative examples of c_i.

Term Selection Functions: DF

- Document frequency (DF):
  - Number of documents in which t_k appears
- Applying DF:
  - Remove terms with DF below some threshold
- Intuition:
  - Very rare terms won't help with categorization
    - or not useful globally
- Pros: Easy to implement, scalable
- Cons: Ad-hoc, low DF terms 'topical'

Term Selection Functions: MI

- Pointwise Mutual Information (MI)

$$PMI(t_k, c_i) = \log \frac{P(t_k, c_i)}{P(t_k)P(c_i)}$$

- $MI(t, c) = 0$ if t and c are independent

- Issue: Can be heavily influenced by marginal probability
  - Problem comparing terms of differing frequencies

Term Selection Functions: IG

- Information Gain:
  - Intuition: Transmitting Y, how many bits can we save if both sides know X?
  - $IG(Y, X) = H(Y) - H(Y|X)$

$$IG(t_k, c_i) = P(t_k, c_i)\log\frac{P(t_k, c_i)}{P(t_k)P(c_i)} + P(\overline{t_k}, c_i)\log\frac{P(\overline{t_k}, c_i)}{P(\overline{t_k})P(c_i)}$$

Global Selection

- Previous measures compute class-specific selection
- What if you want to filter across ALL classes?
  - an aggregate measure across classes
    - Sum:

$$f_{sum}(t_k) = \sum_{i=1}^{|C|} f(t_k, c_i)$$

    - Average:

$$f_{avg}(t_k) = \sum_{i=1}^{|C|} f(t_k, c_i) P(c_i)$$

    - Max:

$$f_{max}(t_k) = \max_{c_i} f(t_k, c_i) P(c_i)$$

|C| is the number of classes

Which function works the best?

- It depends on
  - Classifiers
  - Type of data
  - …

- According to (Yang and Pedersen 1997)
  - $\{\chi^2$, IG$\} > \{$#avg$\} >> \{$MI$\}$

Feature weighting

Feature weights

- Feature weight in {0,1}: same as DR

- Feature weight in $\mathbb{R}$: iterative approach:
  - Ex: MaxEnt

➔ Feature selection is a special case of feature weighting.

Feature values

- Term frequency (TF): the number of times that t_k appears in d_i.
- Inverse document frequency (IDF): $\log(|D|/d_k)$, where d_k is the number of documents that contain t_k.

- TF-IDF = TF * IDF

- Normalized TFIDF:

$$w_{ik} = \frac{\text{TF-IDF}(d_i, t_k)}{Z}$$

Summary so far

- Curse of dimensionality ➔ dimensionality reduction (DR)

- DR:
  - Feature extraction
  - Feature selection
    - Wrapping method
    - Filtering method: different functions

Summary (cont)

- Functions:
  - Document frequency
  - Information gain
  - Gain ratio
  - Chi square
  - …

Additional slides

Information gain**

$$\sum_i IG(t_k, c_i)$$

$$= \sum_{c \in C} \sum_{t \in \{t_k, \bar{t_k}\}} P(t,c) log \frac{P(t,c)}{P(c)P(t)}$$

$$= \sum_{c \in C} \sum_t P(t,c) log P(c|t)$$

$$- \sum_c \sum_t P(t,c) log P(c)$$

$$= -H(C|T) - \sum_c ((log P(c)) \sum_t P(t,c))$$

$$= -H(C|T) + H(C) = IG(C,T)$$

More term selection functions**

Relevancy score:

$$RS(t_k, c_i) = log\frac{P(t_k|c_i)+d}{P(\bar{t_k}|\bar{c_i})+d}$$

Odds Ratio:

$$OR(t_k, c_i) = \frac{P(t_k|c_i)P(\bar{t_k}|\bar{c_i})}{P(\bar{t_k}|c_i)P(t_k|\bar{c_i})}$$

More term selection functions**

GSS coefficient:

$$GSS(t_k, c_i) = P(t_k, c_i)P(\bar{t_k}, \bar{c_i}) - P(t_k, \bar{c_i})P(\bar{t_k}, c_i)$$

NGL coefficient: N is the total number of docs

$$NGL(t_k, c_i) = \frac{\sqrt{N}\ GSS(t_k, c_i)}{\sqrt{P(t_k)P(\bar{t_k})P(c_i)P(\bar{c_i})}}$$

Chi-square: (one of the definitions)

$$\chi^2(t_k, c_i) = NGL(t_k, c_i)^2 = \frac{(ad-bc)^2 N}{(a+b)(a+c)(b+d)(c+d)}$$