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Machine-Translated Text Detection in a Collection of Russian Scientific Papers

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Machine-Translated Text: Why So Serious?

- Recent advances in the field of statistical machine translation (SMT) lead to high availability of SMT systems on the Web.
- Student papers lack proper analysis by their tutors.
- It is very tempting to find relevant information in English, automatically translate it into Russian, and paste it into the paper “as is”!
- 1’500’000 bachelor and master theses are posted every year.
  - and even more reports and term works
- We need a fast automated way of spotting machine-translated text portions in huge collections of papers.

Machine-Translated Text: Why So Serious?

- SMT often contains grammatical errors or inappropriate words:
  - *First individuals in the system take the maximum number of contacts for any parameter combination.*
  - *Первые лица в системе взять максимальное количество контактов для любой комбинации параметров.*
- We focus on detection of these SMT shortcomings and consider two groups of them:
  - word salad
  - phrase salad
- The algorithm must:
  - work at sentence level
  - be fast (no deep analysis)

Word Salad

- **Word salad** is a “confused or unintelligible mixture of seemingly random words”
  - often attributed to mental diseases: logorrhea, schizophasia etc.
  - may be produced by low-quality SMT systems
- Examples in English:
  - *In worlds with pencils, schools page drink slime.*
  - *Take sharpness filling soda cans.*
  - *Run desk making dinner sunglasses menu.*
- Grammatical features:
  - semantic inconsistency
  - unexpected word combinations

Phrase Salad

- **Phrase salad:** grammatically correct phrases combined together in an improper way
  - occurs in output of SMT systems and text generators
- Examples in Russian:
  - *Все это имеет прямое, а также косвенное влияние на экономическую деятельность и производственных мощностей.*
  - *На практике не существует широкое признание процесс выбора параметра геометрическое распределение.*
  - *Масштаб и положение можно принимать любые значения, совместимых с областью временного ряда.*
- Grammatical features:
  - disagreement in sentence parts

Related Work

- MT quality estimation
  - [Gamon et al., 2005] — multiple syntactic features, French
  - [Avramidis et al., 2011] — PCFG features, English
  - [Aharoni et al., 2014] — presence / absence of POS N-grams, English
- Eliminating low-quality content from parallel corpora
  - [Antonova & Misyurev, 2011] — comparison to another decoder output, Russian + English
- Web spam detection
  - [Grechnikov et al., 2009] — word co-occurrence analysis, Russian
  - [Pavlov & Dobrov, 2011] — Markov chain generator output detection
- Word salad detection
  - [Arase et al., 2013] — language model likelihoods, English + Japanese

Formal Problem Statement

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- $D = \{(x^i, y^i)\}_{i=1}^{m}$ — labeled set of sentences
- $x^i = f(s^i)$ — vector representation of a sentence in $\mathbb{R}^n$
- $s^i = (w_1^i, \dots, w_{k_i}^i)$ — ordered sequence of sentence words
- $y^i \in Y = \{0, 1\}$ — class label
  - 0 for authentic sentences, 1 for machine-translated sentences
- **Problem:** find optimal classification model g: $\mathbb{R}^n \to Y$:
  - with $D = D_L \sqcup D_T$, D_L being a training set, D_T — a test set

$$\hat{g} = \arg\min_{g} \frac{1}{|D_T|} \sum_{i=1}^{|D_T|} [g(s_i) \neq y_i]$$

Solution Design

Solution Design

- Let's estimate the likelihood that a sentence is machine-translated, according to several language models (LMs)…
  - Lexical 2,3-gram LMs trained on authentic texts
  - Lexical 2,3-gram LMs trained on machine-translated texts
  - POS tag 2,3-gram LMs trained on authentic texts
  - POS tag 2,3-gram LMs trained on machine-translated texts
  - word2vec (skip-gram and CBOW) models trained on authentic texts
- … and use these estimates as features for classification task.
  - 2 * 4 + 2 = 10 features in total
- N-gram models with N > 3 have negligible effect on classification performance
  - according to [Arase et al., 2013]

Lexical N-Gram Language Models

Estimated sentence likelihood:

$$\hat{p}_{LM}(s) = \hat{p}_{LM}(w_1, \dots, w_k) = \prod_{i=1}^{k} \hat{p}_{LM}(w_i \mid w_{i-N+1}, \dots, w_{i-1})$$

E.g., for N = 3:

$$\hat{p}_{LM}(w_i \mid w_{i-2}, w_{i-1}) = \frac{count(w_{i-2}w_{i-1}w_i) + 1}{count(w_{i-2}w_{i-1}) + |V_3|}$$

V_3 — set of all corpus 3-grams

Lexical model sentence score:

$$score_{LM}(s) = \frac{1}{k} \log \hat{p}_{LM}(s)$$

POS Tag N-Gram Language Models

- POS tags contain morphological information:
  - part of speech
  - gender, case and number for nouns
  - gender, case and number for adjectives and participles
  - person, case and number for personal pronouns
  - person (or an indicator of infinitive form) for verbs

$$\hat{p}_{POS}(s) = \hat{p}_{LM}\big(h(w_1), \dots, h(w_k)\big)$$

$$h(w) — \text{POS tag for } w$$

$$score_{POS}(s) = \frac{1}{k}\log \hat{p}_{POS}(s)$$

- Lexical LM scores are aimed at *word salad* detection
- POS LM scores are aimed at *phrase salad* detection

Word2vec Likelihood Scores

- Skip-gram model sentence likelihood:

$$score_{SG}(s) = \frac{\log \hat{p}_{SG}(s)}{k} = \frac{1}{k} \sum_{i=1}^{k} \sum_{j=1}^{k} \mathbb{I}_{[1 \le |i-j| \le 5]} \log \hat{p}_{SG}(w_j | w_i)$$

- Continuous-bag-of-words model sentence likelihood:

$$score_{CBOW}(s) = \frac{1}{k} \sum_{j=1}^{k} \log \hat{p}_{CBOW}(w_j | s_{-j})$$

$$s_{-j} = (w_{j-5}, \dots, w_{j-1}, w_{j+1}, \dots, w_{j+5})$$

- $\hat{p}_{SG}$ and $\hat{p}_{CBOW}$ are obtained directly from pre-trained word2vec models

Experiments

Data Preparation

- 300K human-written sentences in Russian
  - jurisprudential and sociological papers
- 300K English sentences machine-translated into Russian
  - papers of the same domain
  - translated into Russian with one of popular online SMT systems
- 1M articles from Russian Wikipedia
  - short articles filtered out
  - used for word2vec training only
- Separate language model and classifier training
  - 200K + 200K sentences for language model training
  - 100K + 100K sentences for classifier training and validation

Experiment Setting

- Filtering and preprocessing
  - Russian sentences containing non-Cyrillic words filtered out
  - sentences split into tokens
  - words lowercased, punctuation removed
  - special token for numbers
  - unknown words filtered out
- *pymorphy2* for POS tags
- *gensim* for word2vec training
- *scikit-learn* for classification
  - best performance with RandomForestClassifier on 100 trees

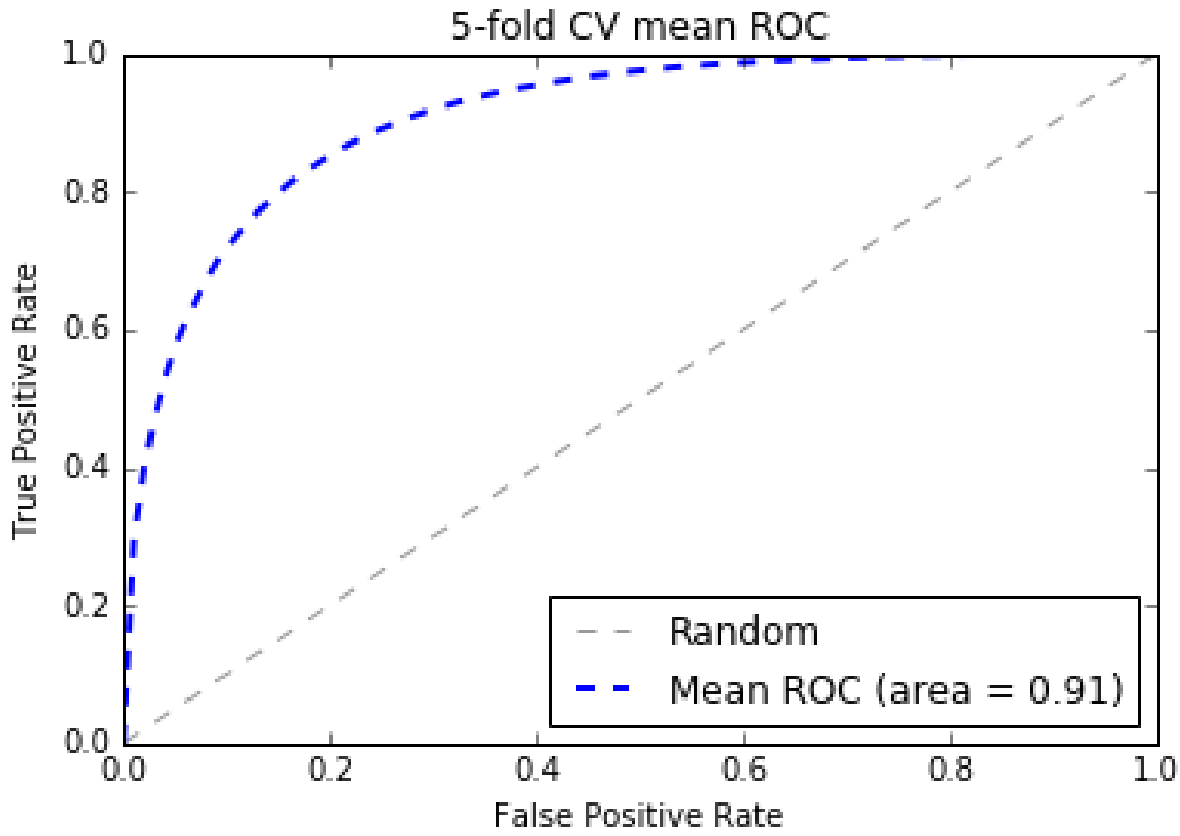
Experiment Results: Overall Performance

- Validation technique:
  - 5-fold cross-validation on the training set
- Performance measures:
  - precision, recall, F1 and AUC ROC

Features	F1	AUC ROC
Lexical 2,3-gram LMs (baseline)	0.754	0.816
POS tag 2,3-gram LMs	0.727	0.804
word2vec LMs	0.643	0.673
Lexical 2,3-gram + POS tag 2,3-gram	0.826	0.907
Lexical 2,3-gram + POS tag 2,3-gram + word2vec	**0.832**	**0.912**

Features	Prec	Rec
Lexical 2,3-gram + POS tag 2,3-gram + word2vec	**0.836**	**0.828**

Experiment Results: Overall Performance



Experiment Results: Feature Importance

- Scores obtained from the trained classifier

Feature	Importance ratio, %
Lexical 2-gram score (MT texts)	26.8
POS tag 3-gram score (authentic texts)	13.4
POS tag 3-gram score (MT texts)	11.5
POS tag 2-gram score (MT texts)	8.0
POS tag 2-gram score (authentic texts)	7.5
CBOW score	7.5
Lexical 3-gram score (MT texts)	6.9
Skip-gram score	6.4
Lexical 2-gram score (authentic texts)	6.2
Lexical 3-gram score (authentic texts)	5.9

Experiment Results: False Positive Errors

- Examples:
  - *Сопоставление с результатами натурного эксперимента.*
  - *При всей своей строгости и лаконичности эта модель обладает существенным недостатком — она является существенно эксплицитной.*
  - *Так, мысль Раскольникова, что, убив ростовщицу, он уничтожает только «вошь», паразита и, таким образом, совершает не столько преступление, сколько благодеяние, опровергается рядом обстоятельств.*
- Most common causes:
  - words and combinations with no occurrences in the training corpus
  - out-of-domain words
  - personal names

Experiment Results: False Negative Errors

- Examples:
  - *В среднем работал по 10 часов в день и 20 процентов работали по 12 часов в день.*
  - *Этот курс был запущен полностью практически между иностранными группами по 4-6 человек.*
  - *Преимущества РТС, в частности, темпы и уровни рынка они приводят.*
- Most common causes:
  - low rate of inappropriate translation
  - low rate of phrase salad
  - inconsistency that may be detected only by syntactic parsing

Conclusion & Future Plans

Conclusion & Future Plans

- The method is feasible for detection of machine-translated text at sentence level.
- Different language models can catch specific linguistic phenomena occurring in the output of SMT systems.
- Future plans:
  - LM training on corpora of higher quality and richness
  - accurate tuning of the method parameters
  - experiments on the output of rule-based MT systems
  - adaptation of the approach for the task of machine-generated text detection (output of context-free-grammar generators etc.)

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Thanks for your attention

Questions / Comments?