Multi-Objective Optimization Problems in Statistical Machine Translation

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Introduction

There are 6000 languages in the world.

MACHINE TRANSLATION

Our interest:
Multi-objective Optimization for building these software systems

Hay 6.000 lenguas en el mundo.

Statistical Machine Translation

A bit of History
1960s-now:
Rule-Based Machine Translation
e.g. SYSTRAN
2000s-now:
Statistical Machine Translation
e.g. Google Translate, Bing

When I look at an article in Russian, I say: "This is really written in English, but has been coded in some strange symbols. I will now proceed to decode. [1947]

Warren Weaver

Architecture of Statistical Machine Translation

English sentence (e)

Bilingual Text Data → Statistics & Optimization → Probabilistic Models

Spanish sentence (s)

1a) evas dlrow-eht
1b) ⊕ ⏢
2a) dlrow-eht si detcennoc
2b) ⊕ ⏣ ᛒ
3a) hcraeser si tnatropmi
3b) ⏢ ⏣ ⏢
4a) ew eb-ot-mia tseb ni dlrow-eht
4b) ⊕ ⏣ ⏢ ⏢ ⏢

Frequency

⊕ dlrow-eht	3
⏢ dlrow-eht	1
⏣ si	2
ᛒ si	1

Where is the Optimization Problem?
Optimize weights w_k so that s_{pred} is similar to s_{true}
Usually, non-convex piecewise linear objective

$$s_{predict} = \underset{\substack{s \in spanish \\ sentences}}{\operatorname{argmax}} prob(s \mid e) = \underset{\substack{s \in spanish \\ sentences}}{\operatorname{argmax}} \sum_{k=1}^{K} w_k f_k(s,e)$$

$$\text{MAXIMIZE } similarity(s_{pred}, s_{true})$$

Please give us advice!

Better Techniques?

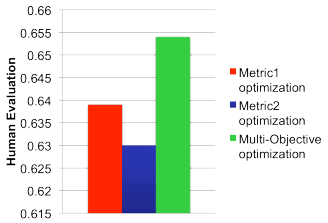
- _____
- _____
- _____

Better Evaluation?

- How to visualize/compare methods with 3+ objectives?
- What to conclude when Pareto Frontiers of diff. methods cross?

Motivation for Multiple Objectives

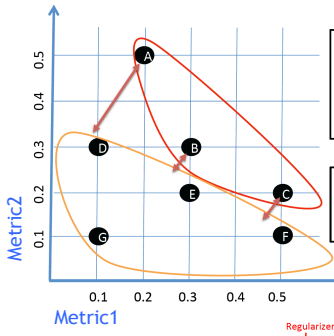
1. Ideally, humans determine similarity(s_{pred},s_{true})
2. But humans cost $$$
3. So we resort to automatic similarity metrics on strings
4. Each metric has pros/cons, so we hope to optimize all



Multi-Objective Optimization Techniques

1. **Lateen Technique:**
   Alternate among single-objective problems.
2. **Linear combination:**
   Combination weights are set to correlate w/ human scores
3. **Pareto Support Vector Machine:**

English (e) → $\sum_{k=1}^{K} w_k f_k(s,e)$ → **Step 0: Generate N-best Spanish hypotheses**



Step 1:
Compute Pareto Frontier on N-best List
Complexity O(#objective * N^2)

Step 2:
Find w separating Pareto vs. Non-Pareto

Intuition:
Translations on Pareto Front deserve higher probabilities

$$\min_{w} \|w\|^2 + c\sum_{ij}\xi_{ij}$$

(Regularizer, Slack)

$$\text{s.t. } w^T\Phi(x,y_i) - w^T\Phi(x,y_j) \geq 1 - \xi_{ij}$$

(Feature vector; Input sentence; Good hypothesis; Poor hypothesis)

$$\forall y_i \in ParetoFront, y_j \notin ParetoFront$$

i.e. score of pareto hypothesis should be higher than non-pareto hypotheses

References

- K. Duh+, Learning to Translation with Multiple Objectives, Proc. of Association for Computational Linguistics (ACL2012)
- B. Sankaran+, Multi-metric Optimization using Ensemble Tuning, Proc. of North American Assoc. for Computational Linguistics (NAACL 2013)