Clustering Affixes:

Applying ML Techniques to Morphological Analysis

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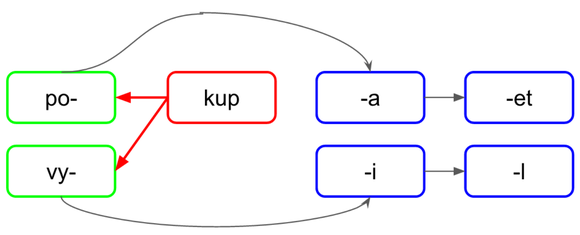
1. Morphological Analysis

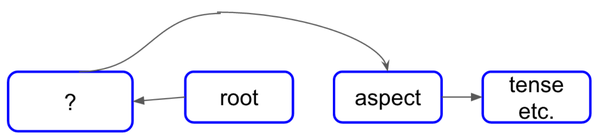
- Group morphemes into Position Classes
- Infer linguistic features associated with the affixes
- Include morphological rules in the grammar

1) Ivan po-kup-a-et sobak-u
   Ivan.NOM PREF1-buy-IMPF-3SG.PRES dog-ACC [rus]
   Ivan is buying a dog.
2) Ivan vy-kup-i-l sobak-u
   Ivan.NOM PREF2-buy-PFV-3SG.M.PST dog.ACC [rus]
   Ivan bought the dog out.

Position classes and Interlinear Glossed Text



Affix graph



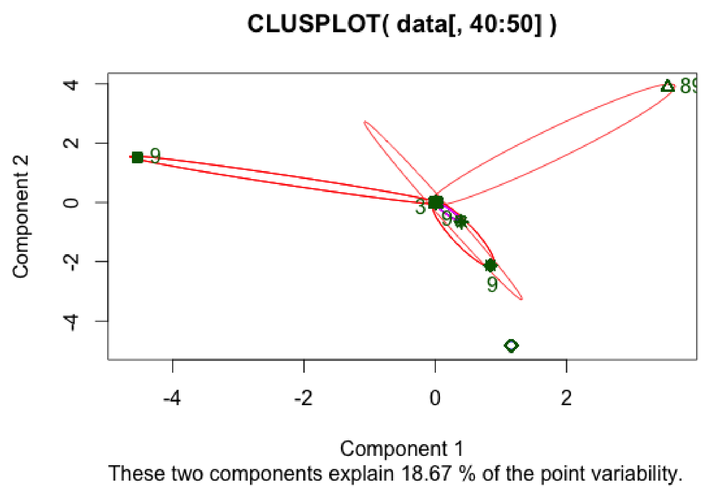
Position classes graph

2. Dataset

- Chintang (ISO-639: ctn) IGT collection, shared by Bickel et al. (2013)
- 9K IGT
- Gold standard exists for morphological rules

3. Clustering affixes

- Use simple classification technique instead of relying on and updating a big graph
  k-means
- Store input information and build the result graph once



These two components explain 18.67 % of the point variability.

2D plot using a subset of features

4. Feature selection

- Orthography
- Gloss
- Right and left context (1 position)
- Linguistic features of the affix
- Prefix or suffix

5. Evaluation

- Precision: how many mistakes in each cluster
  - Pick a cluster (all the assigned labels are the same)
  - Determine which label is the majority label in the corresponding gold labels portion
  - Count how many labels are not the majority label in the corr. gold labels portion
    "false positives"
- Recall: how many things that should be in one cluster are in different clusters
  - Pick a true cluster (all true labels are the same)
  - Determine which label is the majority label in the corresponding assigned labels portion
  - Count how many labels are not the majority label in the corr. assigned labels portion
    "false negatives"
- Excluded from evaluation:
  - Unknown affixes
    not found in the gold file
    constitute a big portion of the data
- Gold labels assigned automatically to datapoints
  mostly based on gloss / orthography

6. Results

Baseline: Graph-based system Wax (2014)

k	24	26
Precision Baseline	75.0	---
Precision k-means	**79.0**	81.0
Recall Baseline	**80.8**	---
Recall k-means	70.6	68.7

(average over 100 k-means runs)

F1 score:

Baseline: 77.4

k-means: 74.2

k-means 26: 73.9

7. Error Analysis

- Recall may be less important.
- There may be errors in the gold standard.
- Need better way to assign gold labels to observations automatically.
- Should use evaluation techniques appropriate for clustering.
  V-measure
- Better feature selection always possible.
- Sparse vectors.
- Recall problems could be solved with the users help
  Active learning

8. Future Work

- Agglomerative clustering and Active learning
  Field linguists have expressed interest in such a system
- Other algorithms may work better on sparse, binary vectors
- Dimensionality reduction
- Evaluation methods for unknown affixes
  Evaluation by parsing

9. Acknowledgments

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References

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