Active learning in sequence labeling

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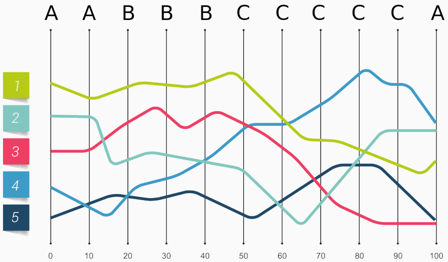
Table of contents

Introduction

Sequence modeling and labeling problem definition

- Sequence of states
- Sequence of observations



Obrázek 1: Sequence representation

Sequence modeling and labeling problem definition

1. Sequence modeling
    - Given a sequence of states/labels and sequence of observations, find a model that the most likely generates the sequences.
2. Sequence labeling
    - Given a sequence of observations, determine an appropriate label/state for each observation.

- Reducing errors by considering relations.

Applications

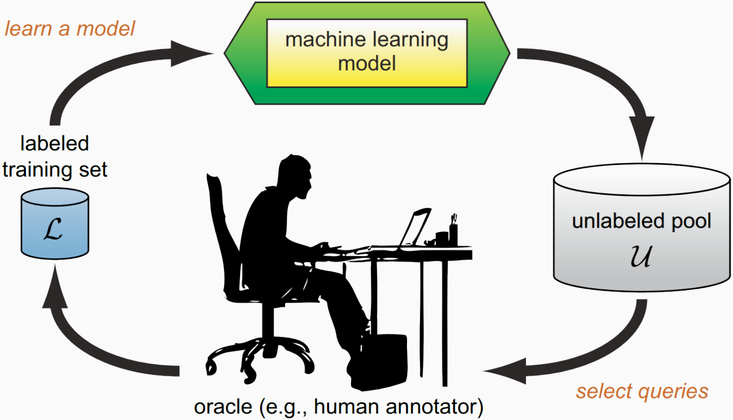
- Handwriting recognition
- Facial expression dynamic modeling
- DNA analysis
- Part-of-speech tagging
- Speech recognition
- Video analysis

Active learning

What is active learning?

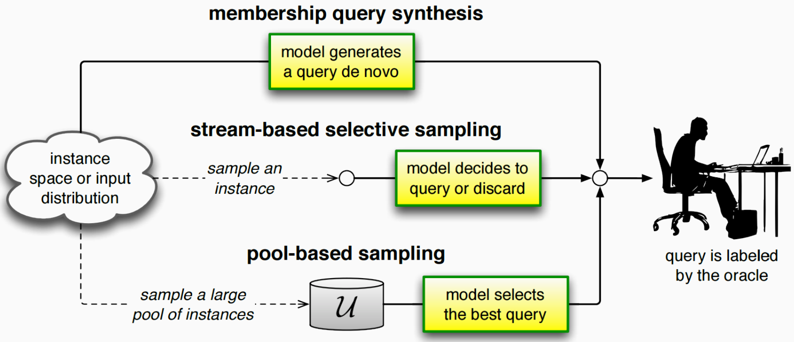
- *The quality of labels makes a huge difference. Garbage in, garbage out.*
- *Obtaining "golden"annotation data can be really expensive.*

What is active learning?



Obrázek 2: Active learning cycle

Scenarios



Obrázek 3: Active learning scenarios

AL algorithm

Data:

L - set of labeled examples

U - set of umlabeled examples

θ - utility function

while *stopping criterion is not met* **do**

1. learn model M from L;
2. for all $x_i \in U : u_{x_i} \leftarrow \theta_M(x_i)$;
3. select example $x^* \in U$ with the highest utility function u_i;
4. query annotator for label of example x^*;
5. move $< y, x^* >$ to L;

end

return L

Algorithm 1: General pool-based AL framework

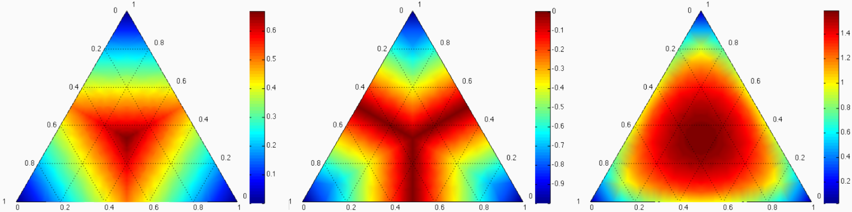
Query strategies frameworks

1. Uncertainty Sampling
2. Query-By-Committee
3. Expected Model Change
4. Expected Error Reduction
5. Variance Reduction
6. Density-Weighted Methods

Frameworks: Uncertainty Sampling

- Simplest, most commonly used
- Intuitive for probabilistic learning model
- Binary problems: choose intance with posterior probability near to 0.5
- Multiclass problems:
  - Least confident - $x^*_{LC} = \arg\max_x 1 - P_\theta(\hat{y}|x)$
  - Margin sampling - $x^*_M = \text{argmin}_x P_\theta(\hat{y}_1|x) - P_\theta(\hat{y}_2|x)$
  - Entropy - $x^*_H = argmax_x - \sum_i P_\theta(y_i|x)\text{log}P_\theta(y_i|x)$

Frameworks: Uncertainty Sampling



(a) least confident (b) margin (c) entropy

Obrázek 4: Uncertainty sampling for three-class classification problem

- Application dependent
- Entropy - minimizing log-loss
- LC + Margin - minimizing classification error

Frameworks: Query-By-Committee

- We maintain a committee $\mathcal{C} = \{\theta_1, ..., \theta_C\}$ of models trained on $\mathcal{L}$
- The most informative query is considered to be the instance about which they most disagree.
- We need to ensure variability of models in the beginning
- Measure of disagreement:
  - Vote entropy - $x^*_{VE} = argmax_x - \sum_i \frac{V(y_i)}{C} \log \frac{V(y_i)}{C}$
  - Kullback-Leibler divergence - $x^*_{KL} = argmax_x \frac{1}{C} \sum_{c=1}^{C} D_{KL}(P_{\theta^{(c)}} || P_C)$

Frameworks: Expected Model Change

- Capable for models using gradient based training.
- Query instance which would cause the largest model change.
- Use a gradient of the objective function $\bigtriangledown \ell_\theta(\mathcal{L})$
- $x^*_{EMC} = \text{argmax}_x \sum_i P_\theta(y_i|x) \parallel \bigtriangledown \ell_\theta(\mathcal{L} \cup < y_i, x >) \parallel$
- Note: $\parallel \bigtriangledown \ell_\theta(\mathcal{L}) \parallel$ should be close to zero therefore we can use an approximation $\parallel \bigtriangledown \ell_\theta(\mathcal{L} \cup < y_i, x >) \parallel \approx \parallel \bigtriangledown \ell_\theta(< y_i, x >) \parallel$

Frameworks: Expected Error Reduction

- Estimate the expected future error of a model trained on $\mathcal{L} \cup < x, y >$
- Methods:
  - Minimizing the excepted 0/1-loss
    $x^* = \text{argmin}_x \sum_i P_\theta(y_i|x)\Big(\sum_{u=1}^{U} 1 - P_{\theta + <x,y_i>}(\hat{y}|x^{(u)})\Big)$
  - Minimizing the excepted log-loss
    $x^* = \text{argmin}_x \sum_i P_\theta(y_i|x)\Big(- \sum_{u=1}^{U} \sum_j P_{\theta + <x,y_i>}(y_j|x^{(u)}) \log P_{\theta + <x,y_i>}(y_j|x^{(u)})\Big)$
- In most cases the most computationally expensive query framework
  - Logistic regression - $\mathcal{O}(ULG)$
  - CRF - $\mathcal{O}(TM^{T+2}ULG)$

Frameworks: Variance Reduction

- Use the bias-variance decomposition
- $E_T[(\hat{y} - y)^2|x] =$
  $E[(y - E[y|x])^2] + (E_{\mathcal{L}}[\hat{y}] - E[y|x])^2 + E_{\mathcal{L}}[(\hat{y} - E_{\mathcal{L}}[\hat{y}])^2]$
- Model dependent framework

Frameworks: Density-Weighted Methods

- Informative instances should not only be those which are uncertain, but also those which are "representative" of the underlying distribution
- Uses one of other query strategies as base query strategy (e.g. uncertainty sampling)
- $x^* = argmax_x \phi_A(x) \times \left(\frac{1}{U} \sum_{u=1}^{U} sim(x, x^{(u)}) \right)^{\beta}$
- The metod is more robust to outliers in dataset.

Active learning problem variants

- Active Learning for Structured Outputs
  - Instance is not represented by a single feature vector, but rather a structure.
  - e.g.: Sequences, trees, grammars.
- Active Feature Acquisition
  - Selection of salient unused features
  - e.g.: Medical tests, sensitive information
- Active Class Selection
  - Learner is allowed to query a known class label, and obtaining each instance incurs a cost.
- Active Clustering
  - Generate (or subsample) instances in such a way that they self-organize into groupings
  - Try to get less overlap or noise than with random sampling

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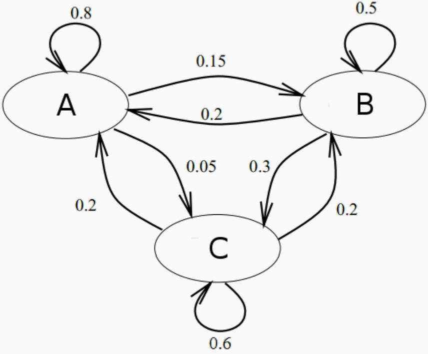
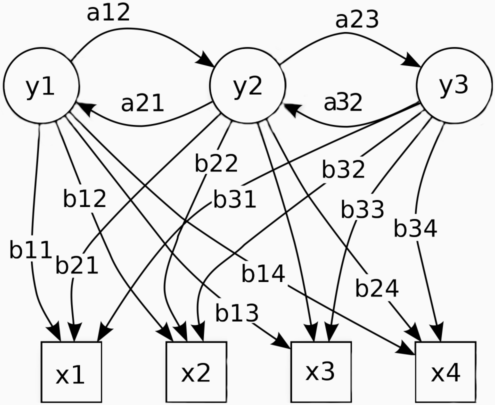
Graphical models

Models: Markov model



Obrázek 5: Markov model/chain

Models: Hidden Markov model



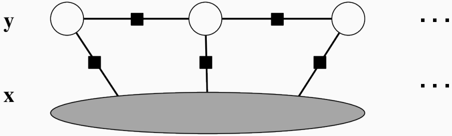
Obrázek 6: Hidden Markov model

Models: Hidden Markov model

$\lambda = (A, B, \pi)$

- Set of hidden states $Y = \{y_1, y_2, ..., y_N\}$, set of observable values $X = \{x_1, x_2, ..., x_M\}$
- Sequence of states $Q = q_1 q_2 q_3 ... q_T$ sequence of outputs $O = o_1 o_2 o_3 ... o_T$
- Transition probability matrix $A = \{a_{ij}\}$
  $a_{ij} = P(q_t = y_j | q_{t-1} = y_i), \quad 1 \leq i, j \leq N$
- Emission probability distribution $B = \{b_{i,j}\}$
  $b_{i,j} = P(o_t = x_j | q_t = y_i), \quad 1 \leq i \leq N, \quad 1 \leq i \leq M$
- Initial probability distribution $\pi = \{\pi_i\}$
  $\pi_i = P(q_1 = y_i), \quad 1 \leq i \leq N$

Models: Conditional random field (linear chain)



Obrázek 7: Linear chain conditional random field

- Discriminative model $P(Y|X)$, we do not explicitly model $P(X)$.
- Perform better than HMMs when the true data distribution has higher-order dependencies than the model.
- $P(Y|X) = \frac{1}{Z(x)} \prod_{t=1}^{T} \exp\Big(\sum_{k=1}^{K} \theta_k f_k(y_t, y_{t-1}, x_t) \Big)$
- $Z(X) = \sum_{Y} \prod_{t=1}^{T} \exp\Big(\sum_{k=1}^{K} \theta_k f_k(y_t, y_{t-1}, x_t) \Big)$

Models: Summary

1. HMM
   - $P(Q,O) \propto \prod_{t=1}^{T} P(q_t|q_{t-1})\, P(o_t|q_t)$

---

2. CRF
   - $$P(Q|O) \propto \frac{1}{Z_O} \prod_{t=1}^{T} \exp\left(\sum_j \lambda_j f_j(q_t, q_{t-1}) + \sum_k \mu_k g_k(q_t, o_t) \right)$$

Active learning in sequence labeling

Uncertainty sampling

- Least confident
  - $x^*_{LC} = \text{argmax}_x\, 1 - P_\theta(\hat{y}|x)$
  - Viterbi path
- Margin sampling
  - $x^*_M = \text{argmin}_x\, P_\theta(\hat{y}_1|x) - P_\theta(\hat{y}_2|x)$
  - N-best aglorithm
- Entropy
  - Token entropy - $x^*_{TE} = \text{argmax}_x -\frac{1}{T}\sum_{t=1}^{T}\sum_{m=1}^{M} P_\theta(y_t = m)\log P_\theta(y_t = m)$
  - Total token entropy
  - Sequence entropy $x^*_{SE} = \text{argmax}_x -\sum_{\hat{y}} P_\theta(\hat{y}|x)\log P_\theta(\hat{y}|x)$
  - N-best sequence entropy $x^*_{SE} = \text{argmax}_x -\sum_{\hat{y}\in\mathcal{N}} P_\theta(\hat{y}|x)\log P_\theta(\hat{y}|x)$

Query by Committee

- Query-by-bagging (each model has unique modified set $\mathcal{L}^{(c)}$)
- Vote entropy - disagreement over Viterbi's paths
  $x^*_{VE} = \text{argmax}_x - \frac{1}{T}\sum_{t=1}^{T}\sum_{m=1}^{M}\frac{V(y_t,m)}{C}\log\frac{V(y_t,m)}{C}$
- Kullback Leibler
  $x^*_{KL} = \text{argmax}_x \frac{1}{T}\sum_{t=1}^{T}\frac{1}{C}\sum_{c=1}^{C} D_{KL}(\theta^{(c)}||\mathcal{C})$
  $D(\theta^{(c)}||\mathcal{C}) = \sum_{m=1}^{M} P_{\theta^{(c)}}(y_t = m) log\frac{P_{\theta^{(c)}}(y_t=m)}{P_{\mathcal{C}}(y_t=m)}$
- Non-normalized variants
- Sequence vote entropy
  $x^*_{SVE} = \text{argmax}_x - \sum_{\hat{y}\in\mathcal{N}^{\mathcal{C}}} P(\hat{y}|x,\mathcal{C})\log P(\hat{y}|x,\mathcal{C})$
- Sequence Kullback-Leibler $x^*_{SKL} = \text{argmax}_x \frac{1}{C}\sum_{c=1}^{C}\sum_{\hat{y}\in\mathcal{N}^{\mathcal{C}}} log\frac{P_{\theta^{(c)}}(\hat{y}|x)}{P_{\mathcal{C}}(\hat{y}|x)}$

Expected Gradient Length

- Exceptation over the N-best labelings.
- $x^*_{EMC} = \text{argmax}_x \sum_{\hat{y} \in \mathcal{N}^C} P_\theta(\hat{y}|x) \parallel \triangledown \ell_\theta(\mathcal{L} \cup < y_i, x >) \parallel$

Expected Error Reduction

- $\mathcal{O}(TM^{T+2}ULG)$ too expensive :(

Density-Weighted Methods

- Information density
  - solves problem that US and QBC are prone to querying outliers
- We need a distance measure for sequences.
  - Kullback-Leibler
  - Euclidean distance
  - Cosine distance
- Drawback: number of required similarity calculations grows quadratically with the number of instances in $\mathcal{U}$.
- Solution: Precompute them.

Semi-supervized active learning in sequence labeling

Fully supervized vs semi-supervized

- FuSAL:
  - Sequence is handled as a whole unit.
  - Sequence-wise vs. token-wise utility functions
- SeSAL
  - Some subsequences can be easily labelled automatically.
  - Decrease labelling effort.
  - Usage of self-training principle.

Fully supervized general algorithm

Data:

B - number of examples to be selected

L - set of labeled examples

U - set of umlabeled examples

θ - utility function

while *stopping criterion is not met* **do**

1. learn model M from L;
2. for all $x_i \in U : u_{x_i} \leftarrow \theta_M(x_i)$;
3. select B examples $x_i \in U$ with highest utility function u_i;
4. annotate sequences using M;
5. query for labels of non-confidential tokens;
6. move newly annotated examples to L;

end

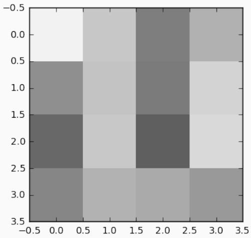
return L

Algorithm 2: General AL framework

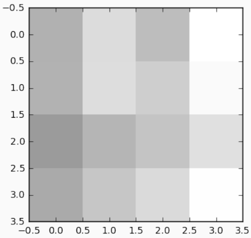
Experiment

Problem definition

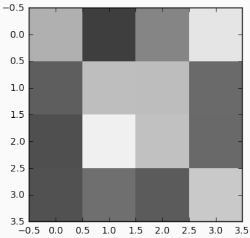
- "Handwritten" letters recognition.
- Each letter is randomly written in one of 6 fonts
- Downscaled to 4x4 pixels
- Letters are orginized in real sentences.



Obrázek 8: A



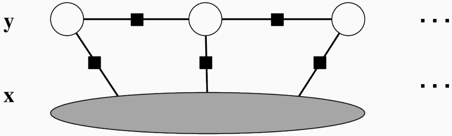
Obrázek 9: B



Obrázek 10: C

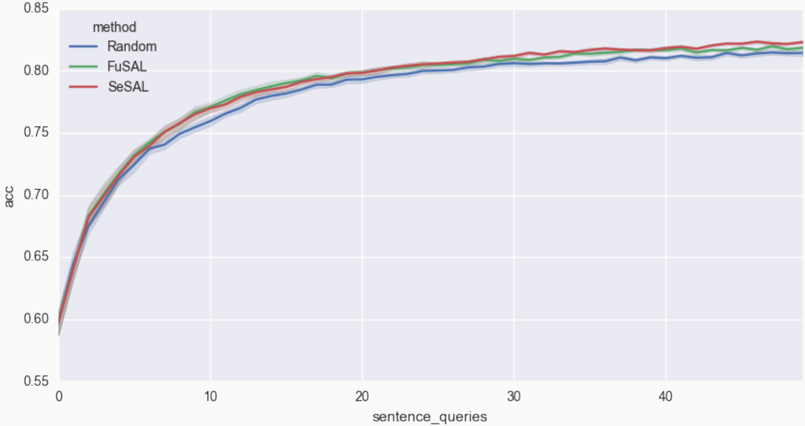
Model and training

- Linear chain conditional random fields.
- 3 labeled sentences in train dataset in the begining .
- Labeled sentences are added to the dataset interatively (50 times).
    - Random choice
    - FuSAL (Least Confident)
    - SeSAL (Least Confident + marginal probability)



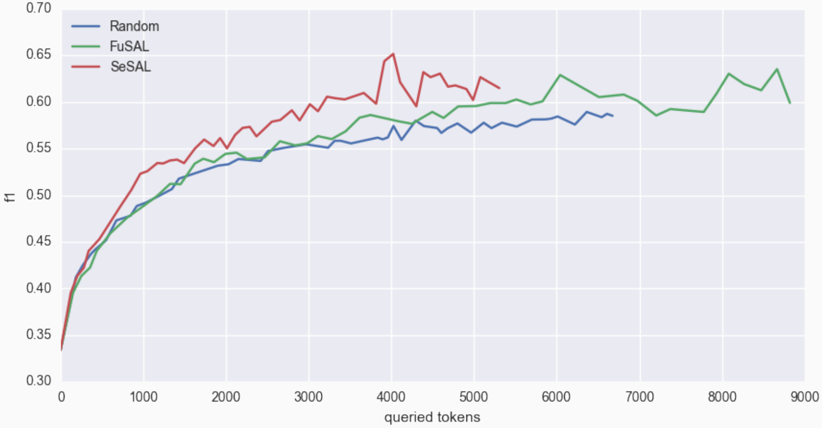
Results

Does it even worth it?

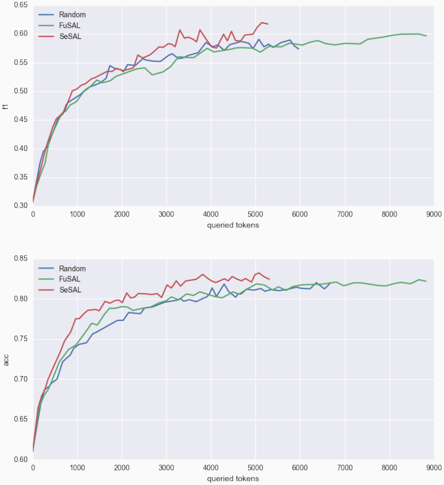


Results

Let's look from another point of view.



Results



Summary

Summary

- It does not work in all cases.
- It can be implementation overhead.

- In the most of cases the active learning helps.
- It can be applied to different structures like sequences or trees
- The combination with semi-supervized learning can lead to rapid save of costs.

- Future work: Different query costs, automatic threshold finding, CT-HMM.

Thank you for your attention.

Questions?