# *OpenTag*: Open Attribute Value Extraction From Product Profiles

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# Motivation

*Alexa*, what are
the flavors of nescafe?

Nescafe Coffee flavors include
*caramel, mocha, vanilla, coconut, cappuccino, original/regular, decaf, espresso,* and *cafe au lait*

# Problem Statement: Extract attribute values from (text of) product profiles

| **Input** Product Profile | | | **Output** Extractions | | |
|---|---|---|---|---|---|
| Title | Description | Bullets | Flavor | Brand | … |
| CESAR Canine Cuisine Variety Pack Filet Mignon & Porterhouse Steak Dog Food (Two 12-Count Cases) | A Delectable Meaty Meal for a Small Canine Looking for the right food … This delicious dog treat contains tender slices of meat in gravy and is formulated to meet the nutritional needs of small dogs. | • Filet Mignon Flavor;<br>• Porterhouse Steak Flavor;<br>• CESAR Canine Cuisine provides complete and balanced nutrition<br>… | 1.filet mignon<br>2.porterhouse steak | cesar canine cuisine | |
| … | … | … | … | | … |

# Characteristics of Attribute Extraction

## Limited semantics, irregular syntax

- Most titles have 10-15 words
- Most bullets have 5-6 words
- Phrases not Sentences
  - Lack of regular grammatical structure in titles and bullets
  - Attribute stacking

1. Rachael Ray Nutrish Just 6 Natural Dry Dog Food, Lamb Meal & Brown Rice Recipe
2. Lamb Meal is the #1 Ingredient

## Open World Assumption

- No Predefined Attribute Value
- New Attribute Value Discovery

1. beef flavor
2. lamb flavor
3. meat in gravy flavor

# Contributions and Prior Work (to do)

# Outline

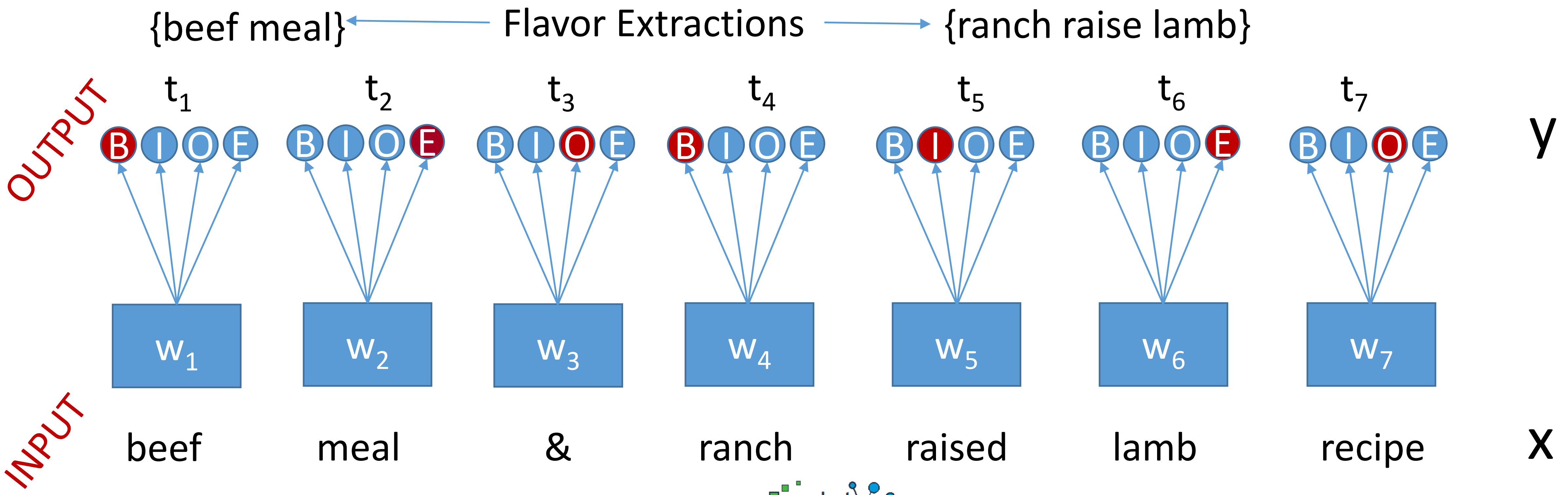
- Sequence Tagging
- Models
- Active Learning
- Experiments and Discussions

# Attribute Extraction as Sequence Tagging

- B — Beginning of attribute value
- I — Inside of attribute value
- O — Outside of attribute value
- E — End of attribute value

$x=\{w_1,w_2,\ldots,w_n\}$ input sequence

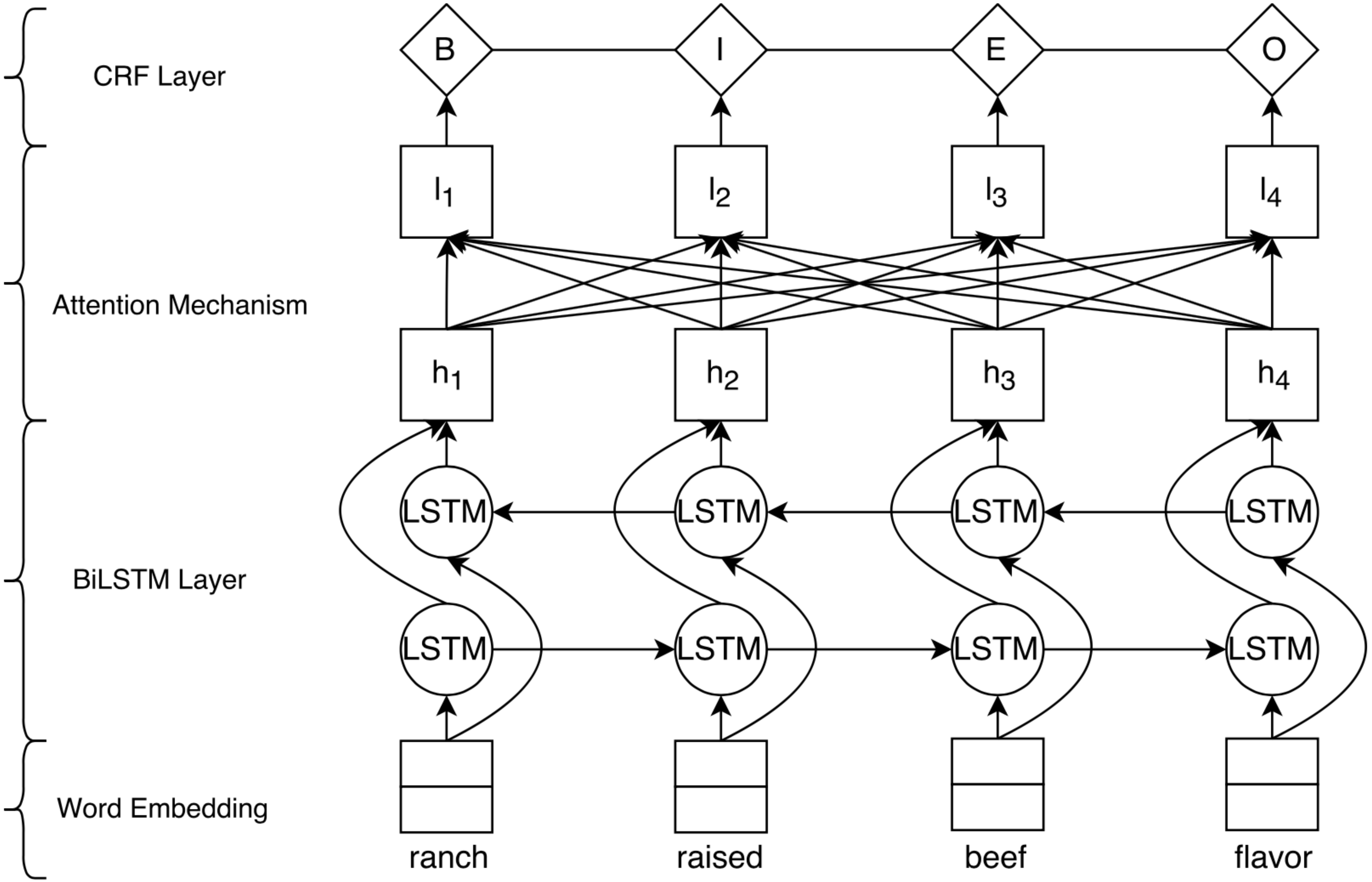
$y=\{t_1,t_2,\ldots,t_n\}$ tagging decision



# Models

- BiLSTM
- BiLSTM + CRF
- Attention Mechanism
- OpenTag Architecture

# OpenTag Architecture

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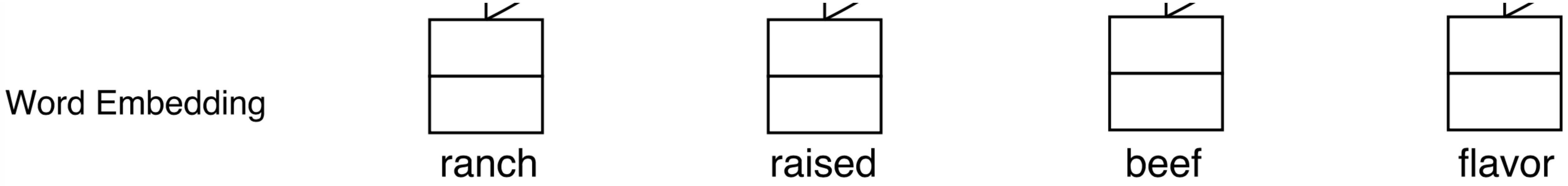
# Word Embedding

- Map words co-occurring in a similar context to nearby points in embedding space
- Pre-trained embeddings learn single representation for each word
  - But 'duck' as a Flavor should have different embedding than 'duck' as a Brand
- OpenTag learns word embeddings conditioned on attribute-tags



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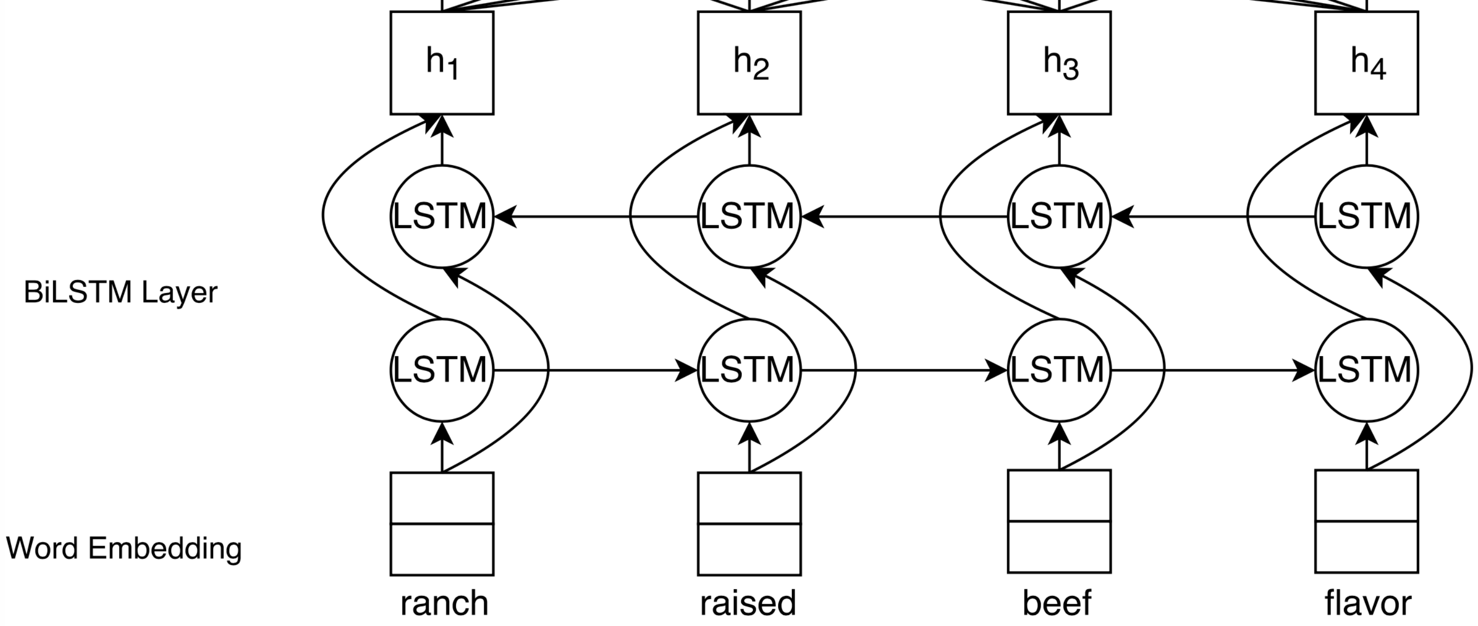
# Bi-directional LSTM




- LSTM (Hochreiter, 1997) capture long and short range dependencies between tokens, suitable for modeling token sequences
- Bi-directional LSTM's improve over LSTM's capturing both forward ($f_t$) and backward ($b_t$) states at each timestep 't'
- Hidden state $h_t$ at each timestep generated as: $h_t = \boldsymbol{\sigma}([b_t, f_t])$

# Conditional Random Fields (CRF)

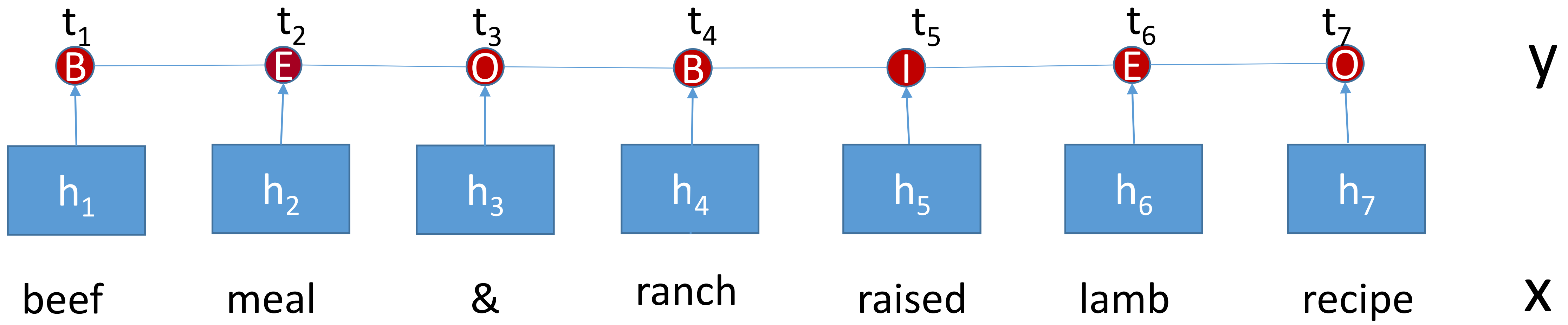
- Bi-LSTM captures dependency between token sequences, but not between output tags
- Likelihood of a token-tag being 'E' (end) or 'I' (intermediate) increases, if the previous token-tag was 'I' (intermediate)
- Given an input sequence **x** = $\{x_1, x_2, \ldots, x_n\}$ with tags **y** = $\{y_1, y_2, \ldots, y_n\}$: linear-chain CRF models:

$$\Pr(y|x;\Psi) \propto \prod_{t=1}^{T} exp\left(\sum_{k=1}^{K} \psi_k f_k(y_{t-1}, y_t, x)\right)$$

# Bi-directional LSTM + CRF

CRF feature space formed by Bi-LSTM hidden states

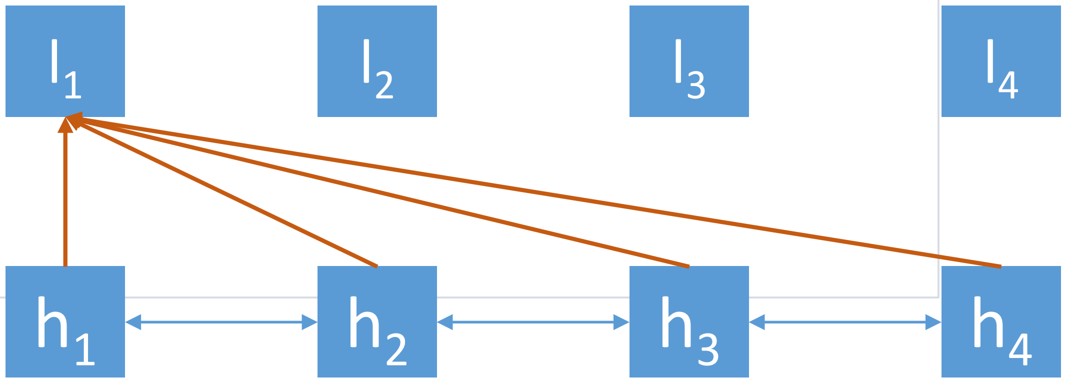
$$\Pr(y|x;\Psi) \propto \prod_{t=1}^{T} exp\left(\sum_{k=1}^{K} \psi_k f_k(y_{t-1}, y_t, \langle h_t \rangle)\right)$$



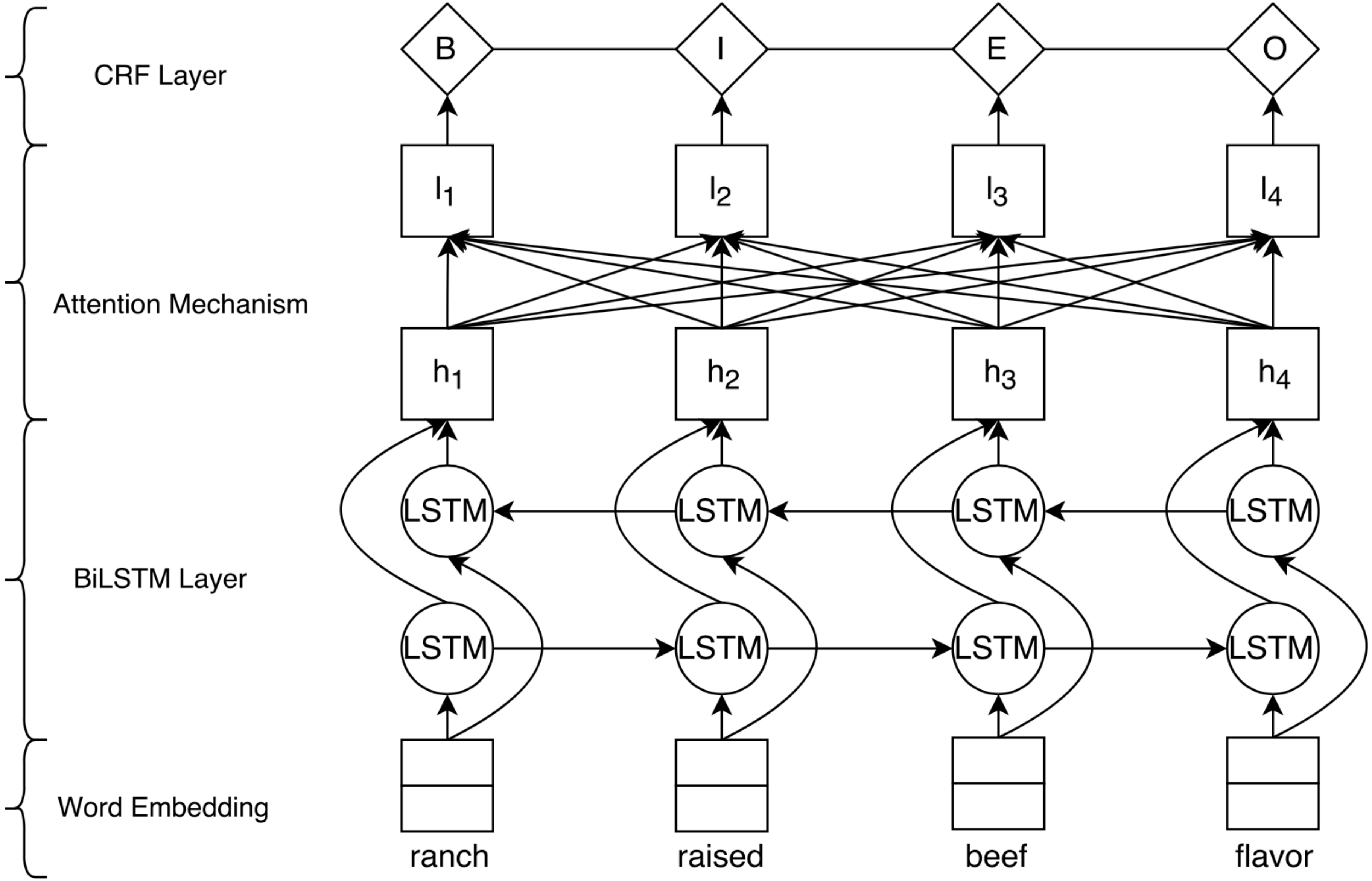
# Attention Mechanism

- Not all hidden states equally important for the CRF
- Focus on important concepts, downweight the rest => *attention*!
- Attention matrix **A** to attend to important BiLSTM hidden states ($h_t$)
  - $\alpha_{t,t'} \in$ **A** captures similarity between $h_t$ and $h_{t'}$
- Attention-focused representation $l_t$ of token $x_t$ given by:

$$l_t = \sum_{t'=1}^{n} \alpha_{t,t'} \cdot h_{t'}$$



# OpenTag Architecture

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# Final Classification

CRF feature space formed by attention-focused representation of hidden states

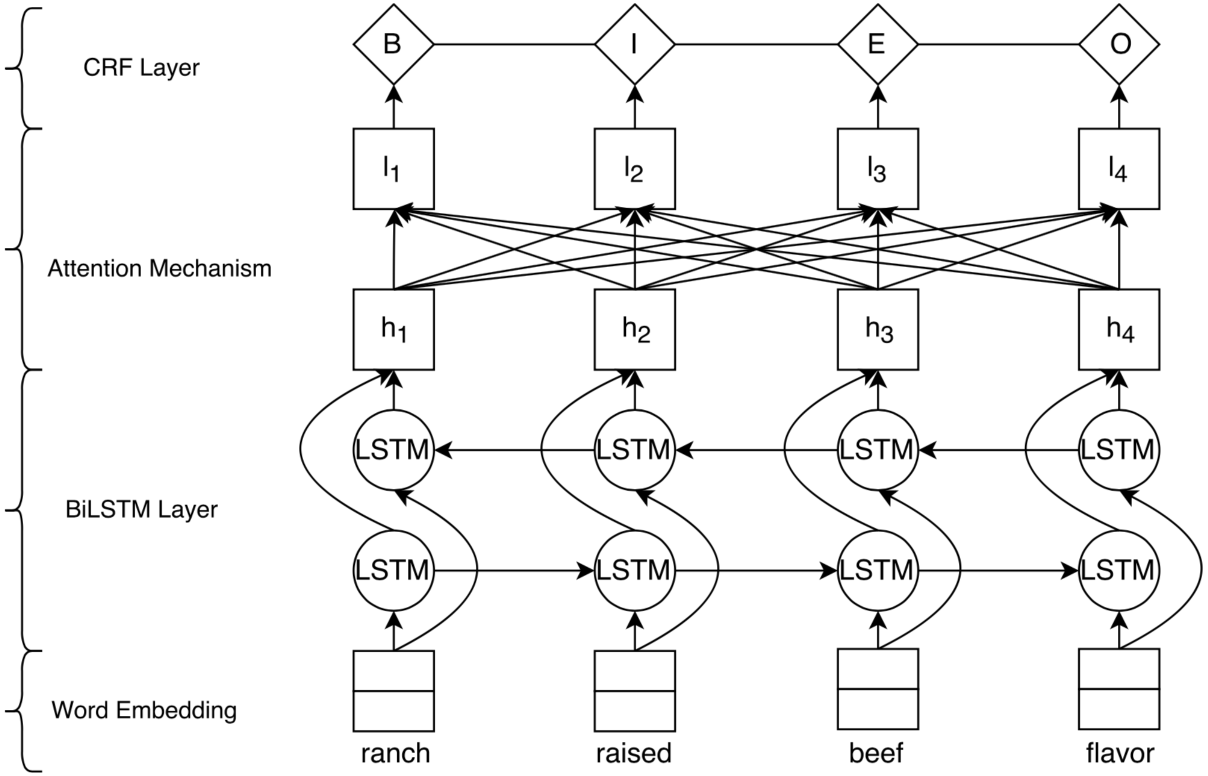
$$\Pr(y|x;\Psi) \propto \prod_{t=1}^{T} exp\left(\sum_{k=1}^{K} \psi_k f_k(y_{t-1}, y_t, \langle l_t \rangle)\right)$$

Maximize log-likelihood of joint distribution

$$L(\Psi) = \sum_{i=1}^{m} \log \Pr(\mathbf{y}_i|\mathbf{x}_i;\Psi)$$

Best possible tag sequence with highest conditional probability

$$y^* = \operatorname{argmax}_y \Pr(y|x;\Psi)$$



# Experimental Discussions: Datasets

| Domain | Profile | Attribute | Training | | Testing | |
|---|---|---|---|---|---|---|
| | | | Samples | Extractions | Samples | Extractions |
| Dog Food (DS) | Title | Flavor | 470 | 876 | 493 | 602 |
| Dog Food | Title | Flavor | 470 | 716 | 493 | 762 |
| | Desc | Flavor | 450 | 569 | 377 | 354 |
| | Bullet | Flavor | 800 | 1481 | 627 | 1179 |
| | Title | Brand | 470 | 480 | 497 | 607 |
| | Title | Capacity | 470 | 428 | 497 | 433 |
| | Title | Multi | 470 | 1775 | 497 | 1632 |
| Camera | Title | Brand | 210 | 210 | 211 | 211 |
| Detergent | Title | Scent | 500 | 487 | 500 | 484 |

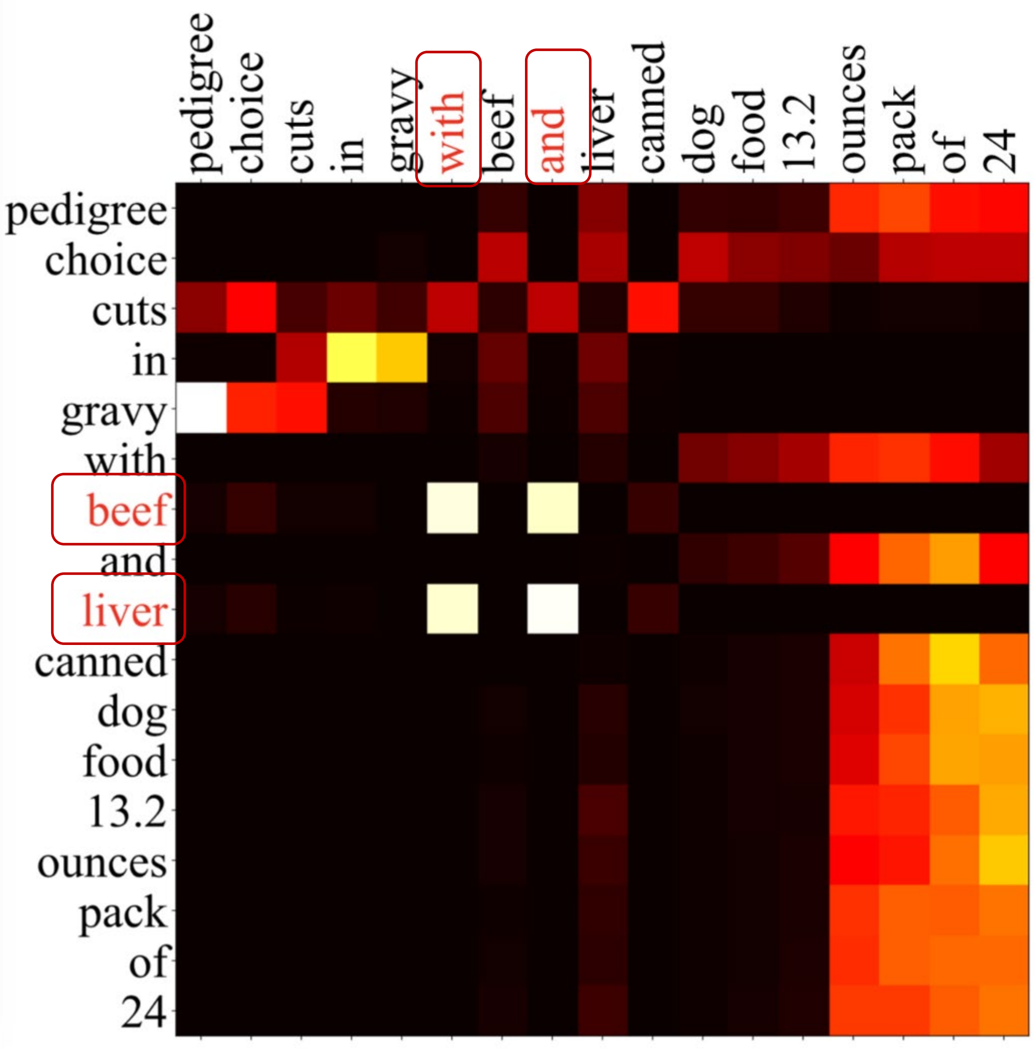
# Results

| Datasets/Attribute | Models | Precision | Recall | Fscore |
|---|---|---|---|---|
| Dog Food: Title<br>Attribute: Flavor | BiLSTM | 83.5 | 85.4 | 84.5 |
| | BiLSTM-CRF | 83.8 | 85.0 | 84.4 |
| | OpenTag | **86.6** | **85.9** | **86.3** |
| Camera: Title<br>Attribute: Brand name | BiLSTM | 94.7 | 88.8 | 91.8 |
| | BiLSTM-CRF | 91.9 | **93.8** | 92.9 |
| | OpenTag | **94.9** | 93.4 | **94.1** |
| Detergent: Title<br>Attribute: Scent | BiLSTM | 81.3 | 82.2 | 81.7 |
| | BiLSTM-CRF | **85.1** | 82.6 | 83.8 |
| | OpenTag | 84.5 | **88.2** | **86.4** |
| Dog Food: Description<br>Attribute: Flavor | BiLSTM | 57.3 | 58.6 | 58 |
| | BiLSTM-CRF | 62.4 | 51.5 | 56.9 |
| | OpenTag | **64.2** | **60.2** | **62.2** |
| Dog Food: Bullet<br>Attribute: Flavor | BiLSTM | 93.2 | 94.2 | 93.7 |
| | BiLSTM-CRF | 94.3 | 94.6 | 94.5 |
| | OpenTag | **95.7** | **95.7** | **95.7** |
| Dog Food: Title<br>Multi Attribute:<br>Brand, Flavor, Capacity | BiLSTM | 71.2 | 67.4 | 69.3 |
| | BiLSTM-CRF | 72.9 | 67.3 | 70.1 |
| | OpenTag | **76.0** | **68.1** | **72.1** |

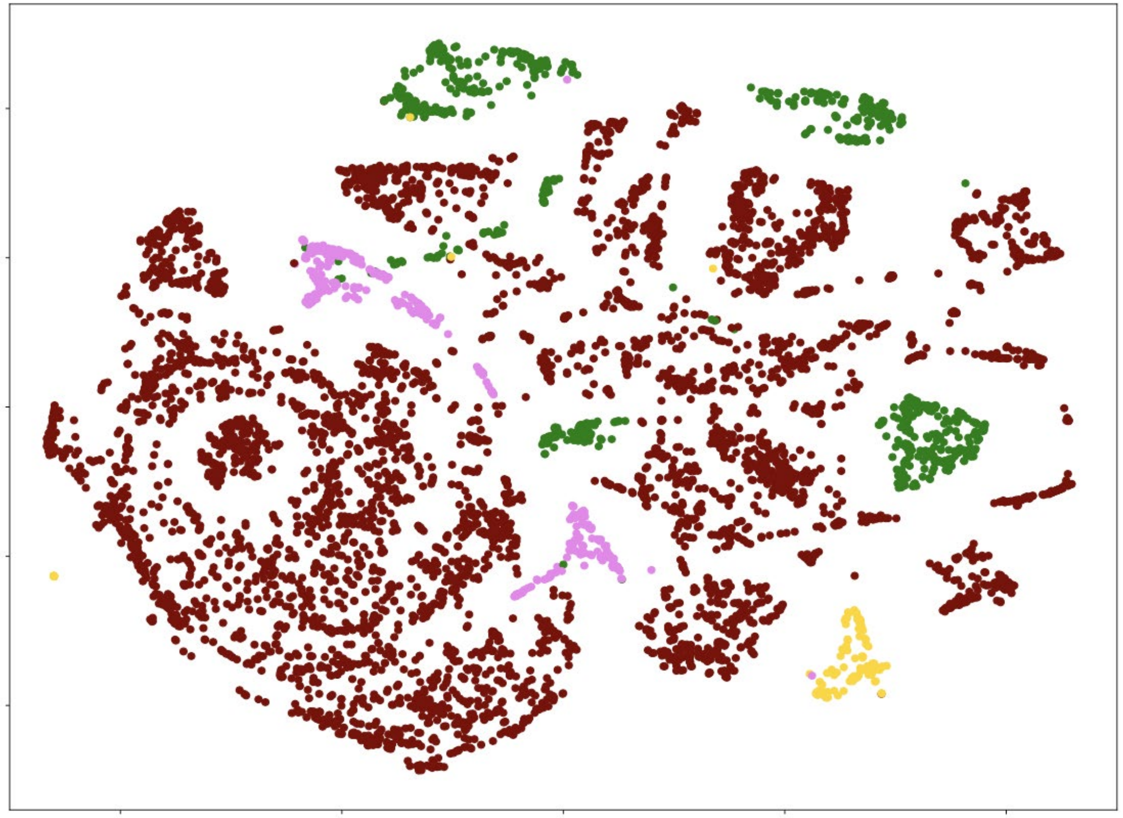
# Discovering new attribute-values not seen during training

| Train-Test Framework | Precision | Recall | F-score |
| --- | --- | --- | --- |
| Disjoint Split (DS) | 83.6 | 81.2 | 82.4 |
| Random Split | 86.6 | 85.9 | 86.3 |

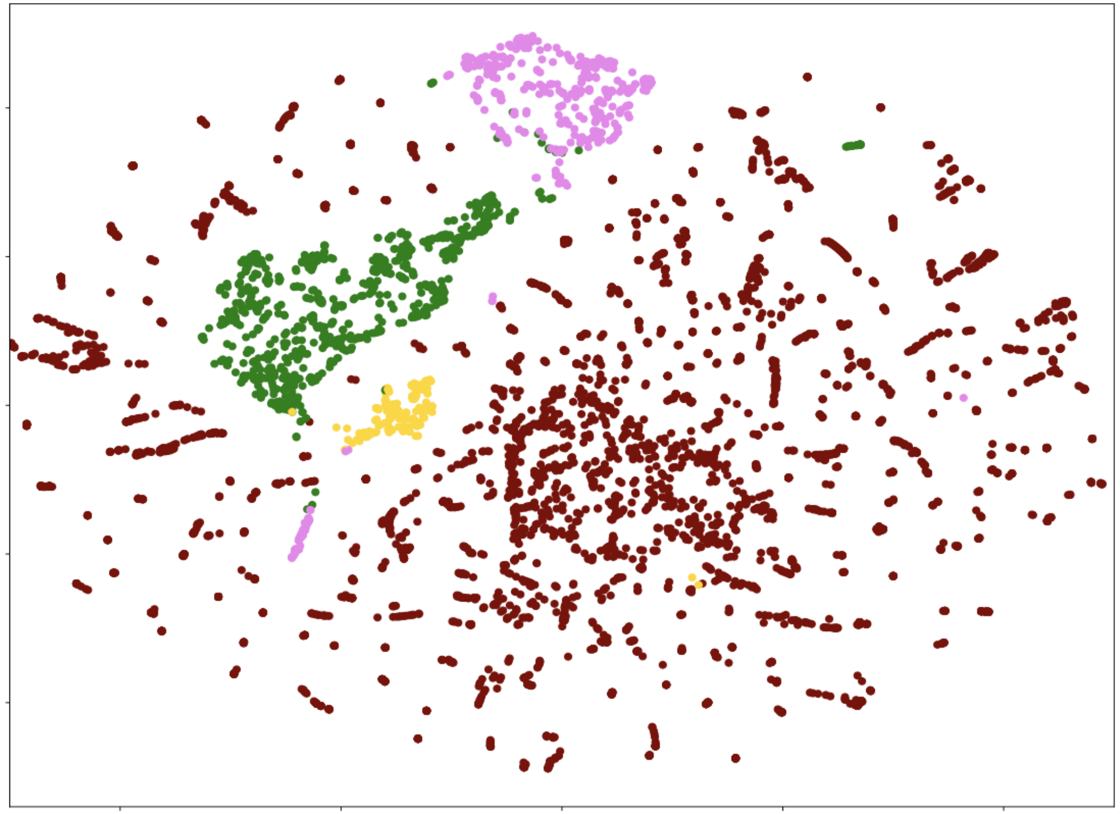
# Intepretability via Attention



# OpenTag achieves better concept clustering

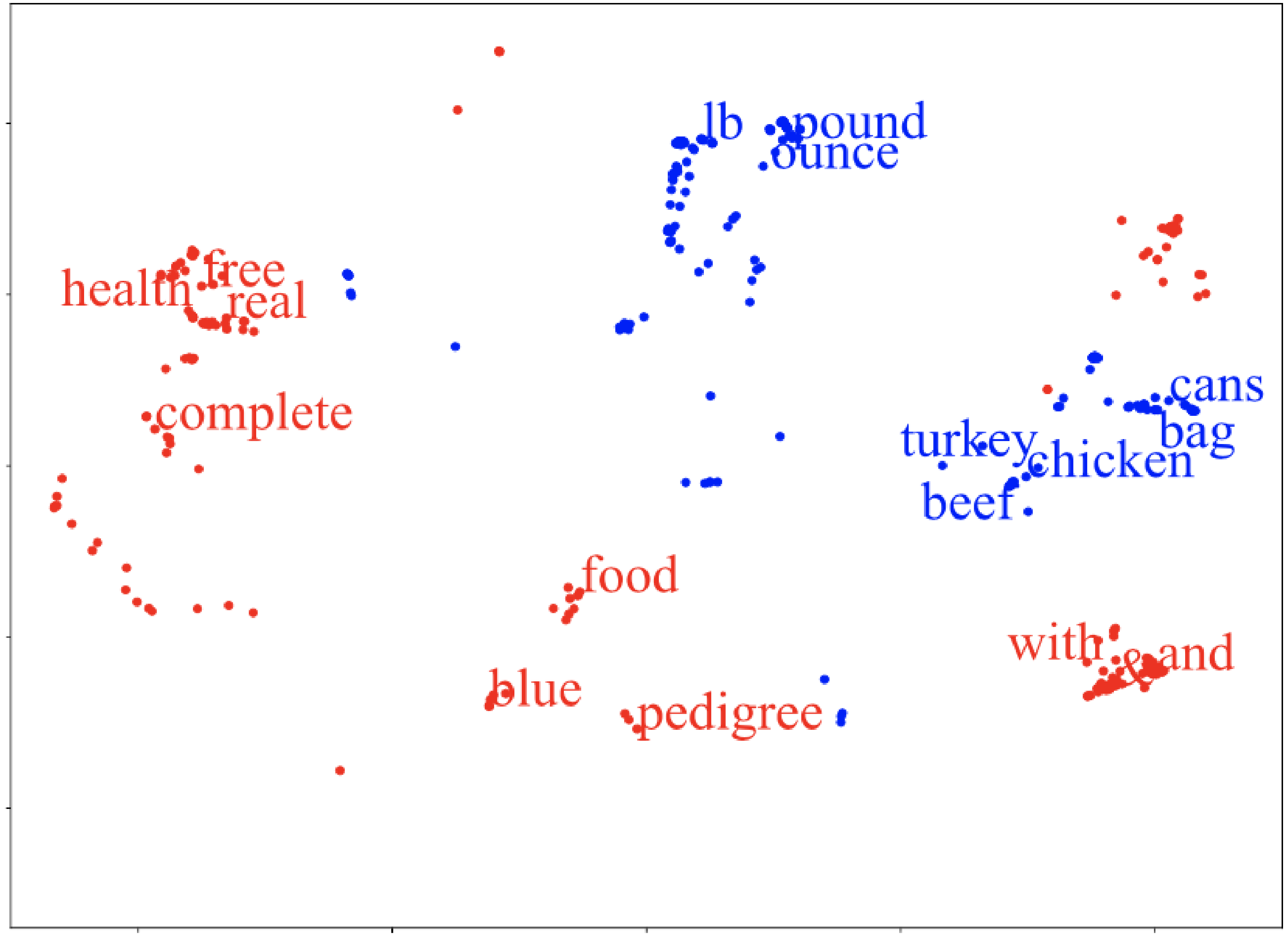


Distribution of word vectors before attention

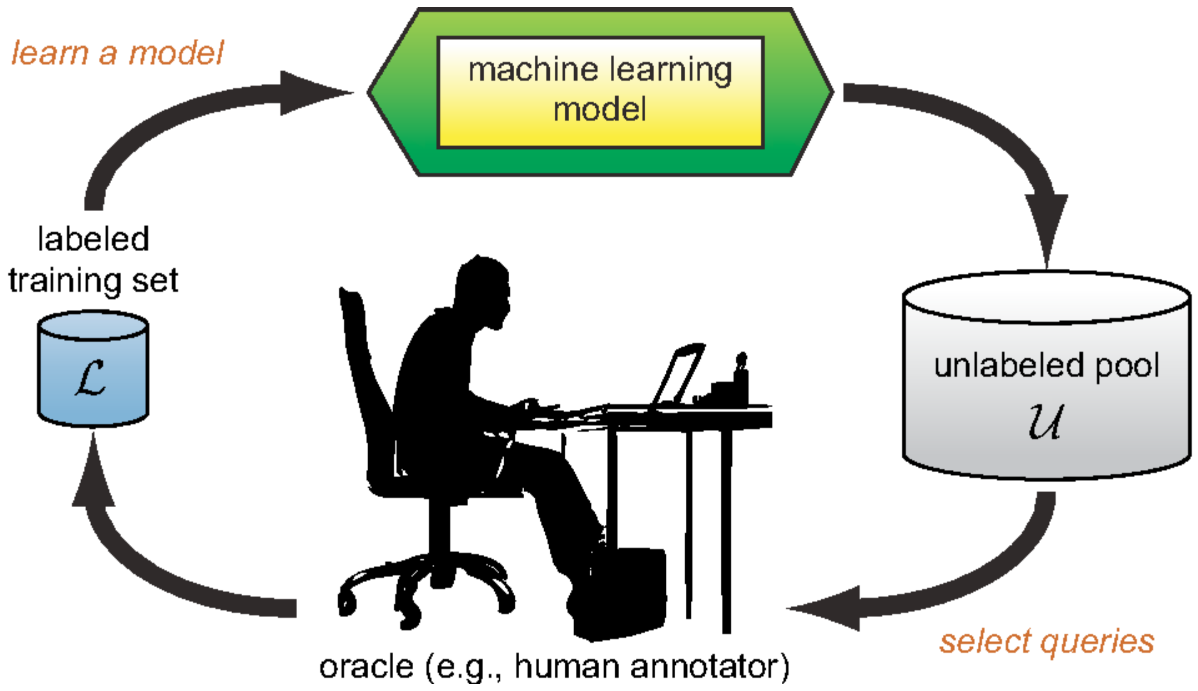


Distribution of word vectors after attention

# Semantically related words come closer in the embedding space



# Active Learning (Settles, 2009)




- Query selection strategy like *uncertainty sampling* selects sample with *highest uncertainty* for annotation
- Ignores difficulty in estimating *individual tags*

# Tag Flip as Query Strategy

- Simulate a committee of OpenTag learners *C* over epochs
- Most informative sample => major disagreement among committee members for tags of its tokens
- Use *dropout mechanism* for simulating committee of learners

| duck | , | fillet | mignon | and | ranch | raised | lamb | flavor |
|---|---|---|---|---|---|---|---|---|
| B | O | B | E | O | B | I | E | O |
| B | O | B | O | O | O | O | B | O |

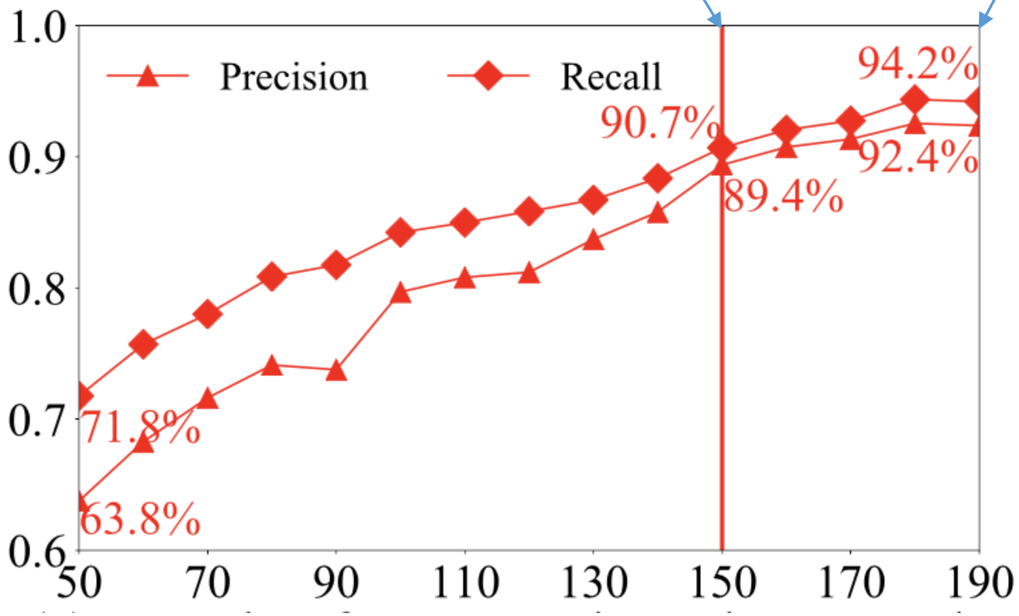
Tag flips = 4

- Most informative sample has *highest tag flips* across all the epochs

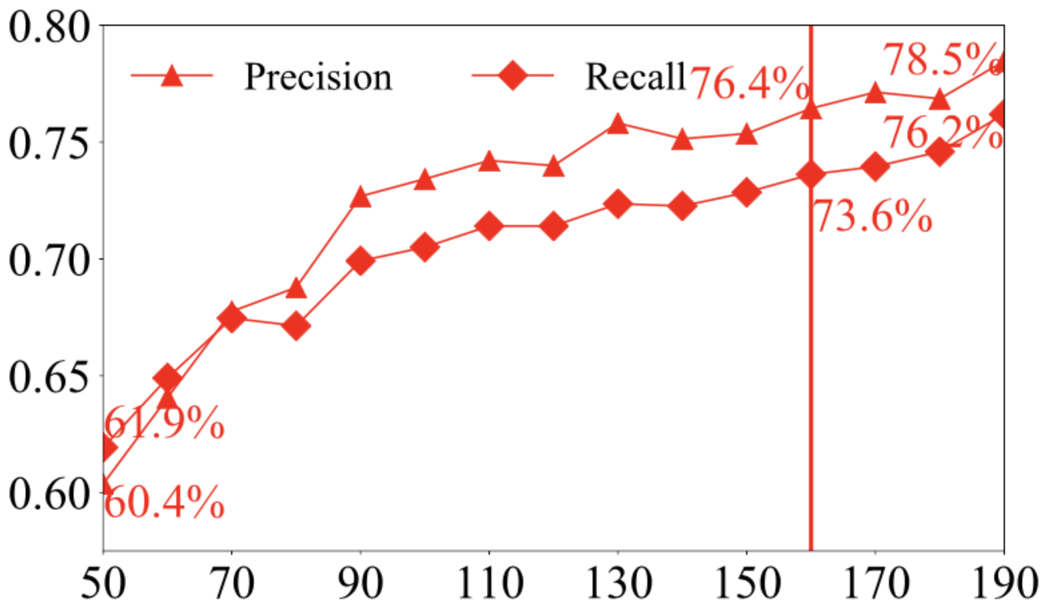
# OpenTag reduces burden of human annotation by 3.3x

150 labeled samples

500 labeled samples




Learning from scratch on detergent data




Learning from scratch on multi extraction

# Production Impact

| | ***Increase*** in Coverage over Existing Production System (%) |
|---|---|
| Attribute_1 | 53 |
| Attribute_2 | 45 |
| Attribute_3 | 50 |
| Attribute_4 | 48 |

# Summary

- OpenTag model based on word embeddings, Bi-LSTM, CRF and attention
  - Open world assumption (OWA), multi-word and multiple attribute value extraction
- OpenTag + Active learning reduces burden of human annotation (by 3.3x)
  - Method of tag flip as query strategy
- Interpretability
  - Better concept clustering, interpretability via attention, etc.

# Backup Slides

# Multiple attribute values

- Predicting multiple attribute values **jointly**

| Attribute | Precision | Recall | F-Score |
|---|---|---|---|
| Brand: Single | 52.6 | 42.6 | 47.1 |
| Brand: Multi | **58.4** | **44.7** | **50.6** |
| Flavor: Single | 83.6 | **81.2** | **82.4** |
| Flavor: Multi | **83.7** | 77.5 | 80.5 |
| Capacity: Single | 81.5 | 86.4 | 83.9 |
| Capacity: Multi | **87.0** | **87.2** | **87.1** |

- Modify tagging strategy to have separate tag-set $\{B_a, I_a, O_a, E_a\}$ for each attribute ‘a’

# Why Sequence Tagging

## Open World Assumption & Label Scaling

- Limited Tags: [BIOE]
- Unlimited Attributes
  - Tag-set not attribute-specific

| | Detected Flavors |
|---|---|
| B E<br>Australian lamb flavor | Australian lamb |
| B B E<br>beef and green lentils | beef, green lentils |

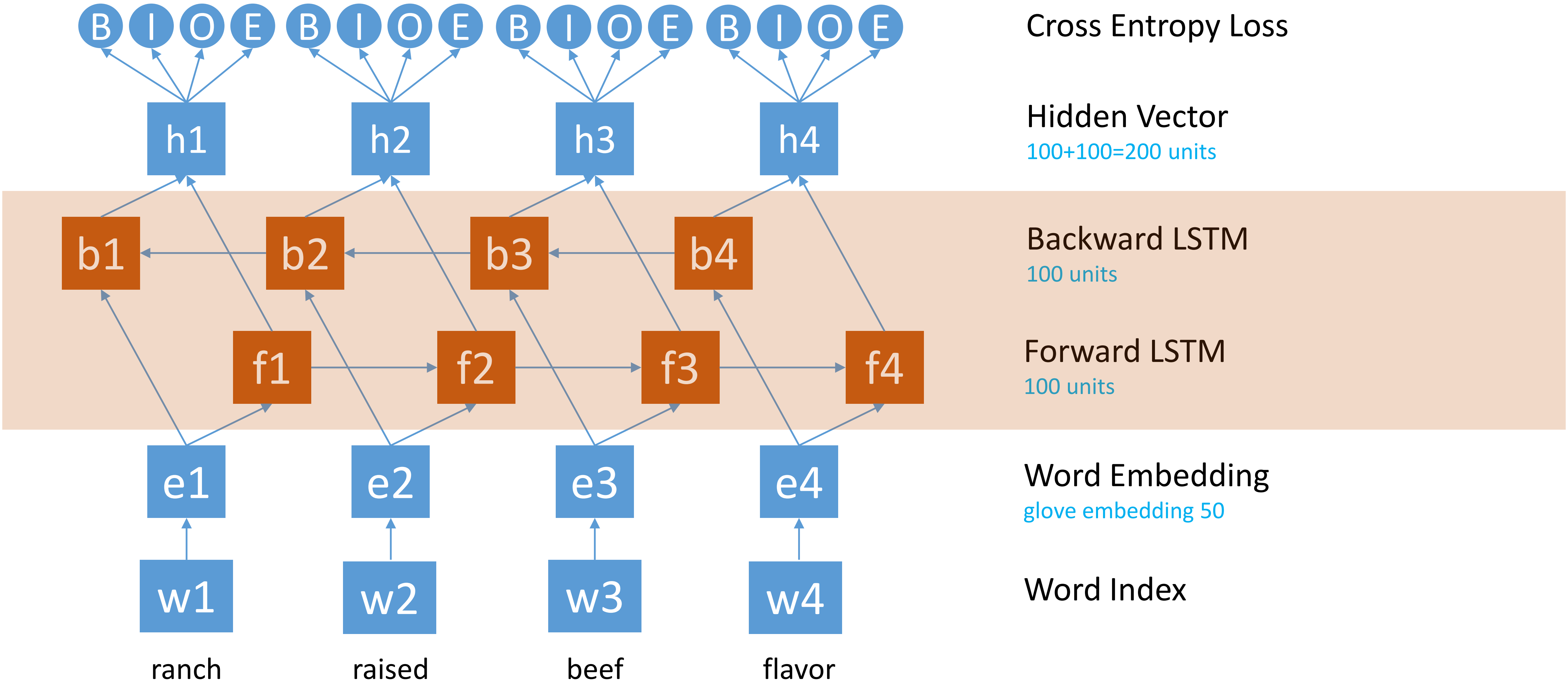
## Discovering multi-word & multiple attribute values

- Semantics of word Itself and surrounding context for chunking

| Tag | Evidence of Tag |
|---|---|
| dry dog food, duck, 10lb | duck itself |
| whitefish flavor | keyword flavor |
| lamb recipe | lamb, keyword recipe |
| beef and green lentils | beef, conjunct word “and” |

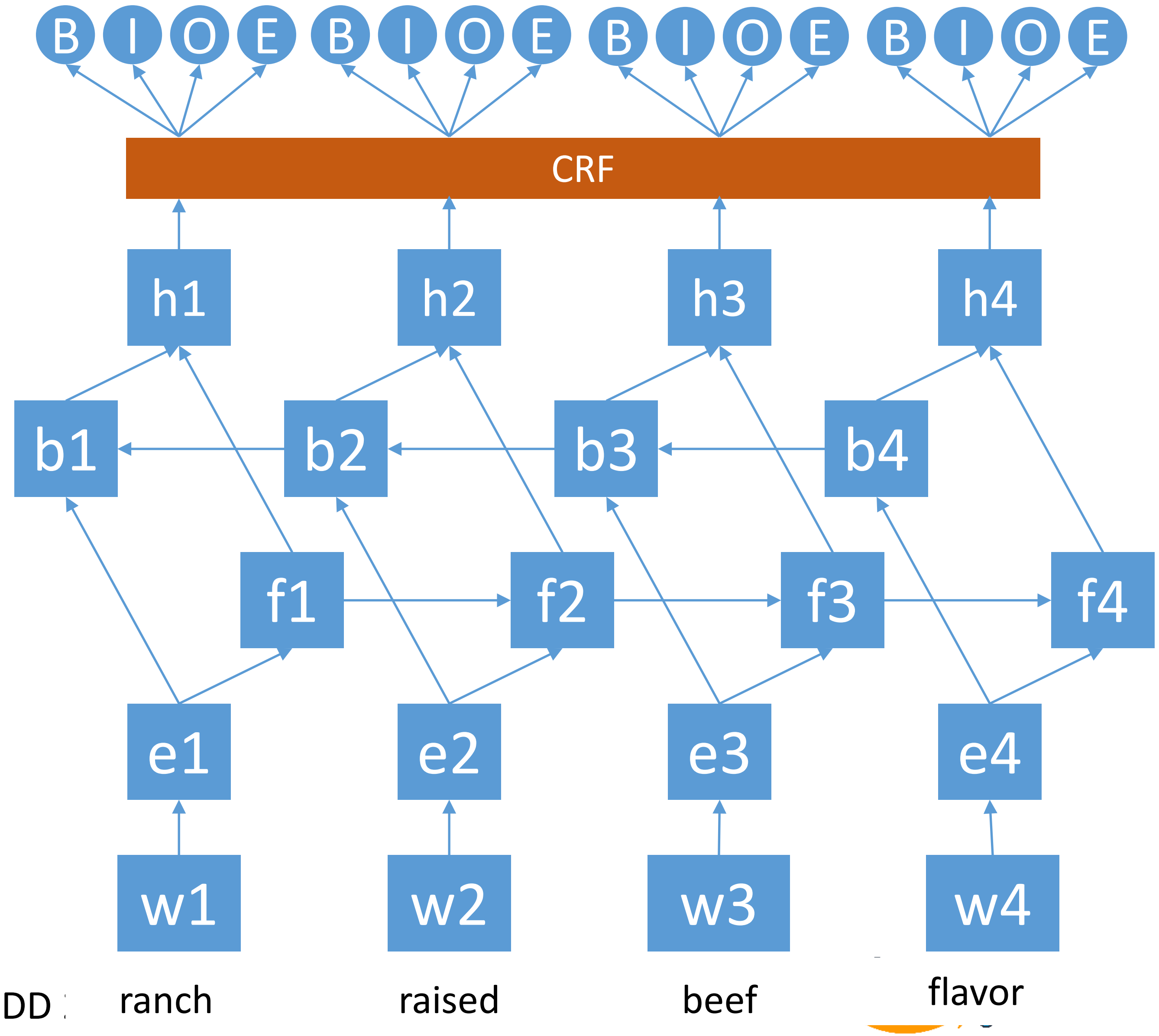
# Bi-directional LSTM

$$\Pr(y_t = k) = \mathrm{softmax}(h_t \cdot W_h)$$



# Bi-directional LSTM + CRF

$$\Pr(y|x;\Psi) \propto \prod_{t=1}^{T} exp\left(\sum_{k=1}^{K} \psi_k f_k(y_{t-1}, y_t, \langle h_t \rangle)\right)$$




Cross Entropy Loss

Conditional Random Fiel

CRF feature space formed by Bi-LSTM hidden states

Forward LSTM
100 units

Embedding
glove embedding 50

Word Index

# Uncertainty Sampling: Probability as Query Strategy

- Select instance with maximum uncertainty
  - Best possible tag sequence from CRF:

$$y^* = \operatorname{argmax}_y \Pr(y|x;\Psi)$$

  - Label instance with maximum uncertainty:

$$Q^{lc}(x) = 1 - \Pr(y^*|x;\Psi)$$

- Considers entire label sequence y, ignores difficulty in estimating individual tags $y_t \in y$

# Tag Flip as Query Strategy

| duck | , | fillet | mignon | and | ranch | raised | lamb | flavor |
|---|---|---|---|---|---|---|---|---|
| B | O | B | E | O | B | I | E | O |
| B | O | B | O | O | O | O | B | O |

Tag flips = 4

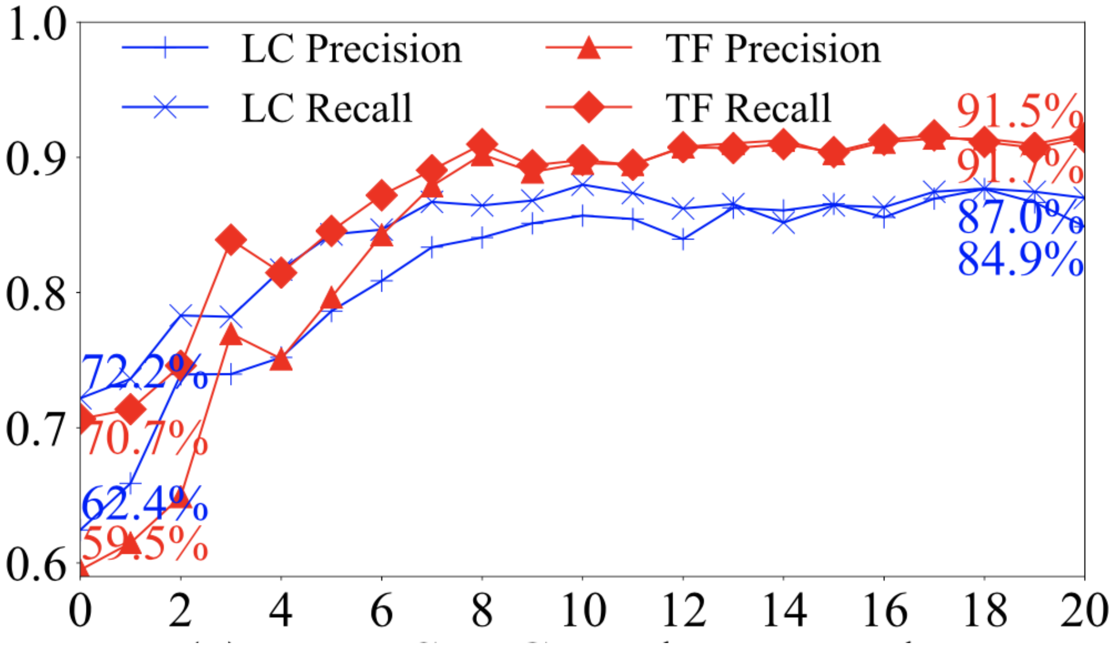
- Most informative instance has maximum tag flips aggregated over all of its tokens across all the epochs:

$$Q^{tf}(x) = \sum_{e=1}^{E} \sum_{t=1}^{n} \mathcal{I}(y_t^*(\Psi^{(e-1)}) \neq y_t^*(\Psi^{(e)}))$$

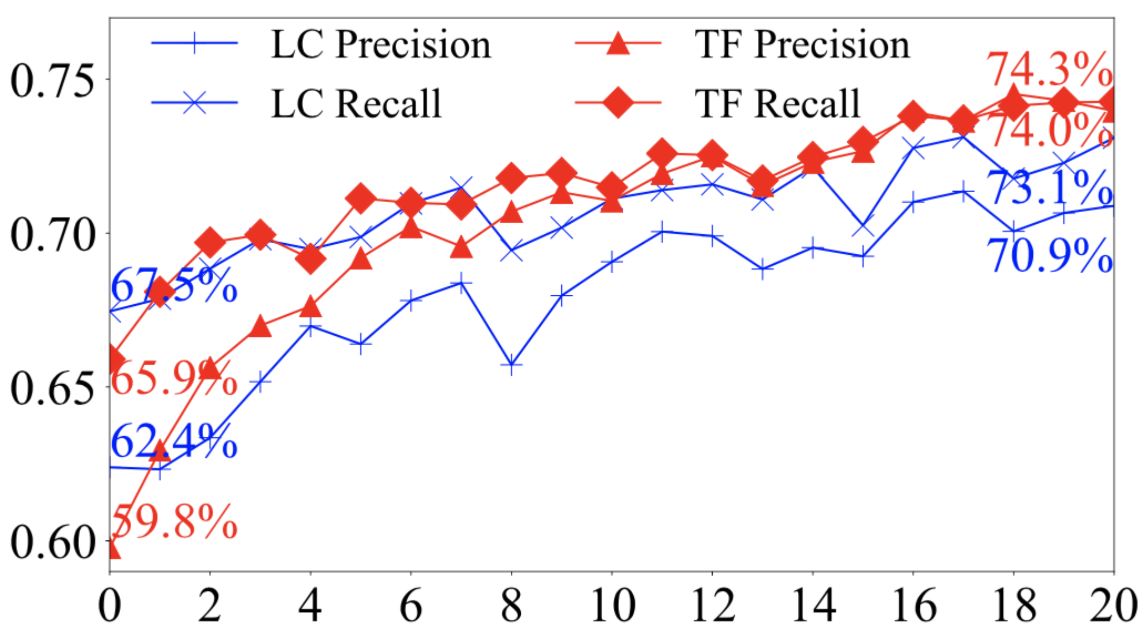
- Top *B* samples with the highest number of flips are manually annotated with tags

# Experiments and Discussions

# Active Learning: Tag Flip better than Uncertainty Sampling




TF v.v. LC on detergent data




TF v.v. LC on multi extraction