

Sentiment Classification of Chinese Contrast Sentences

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Outline

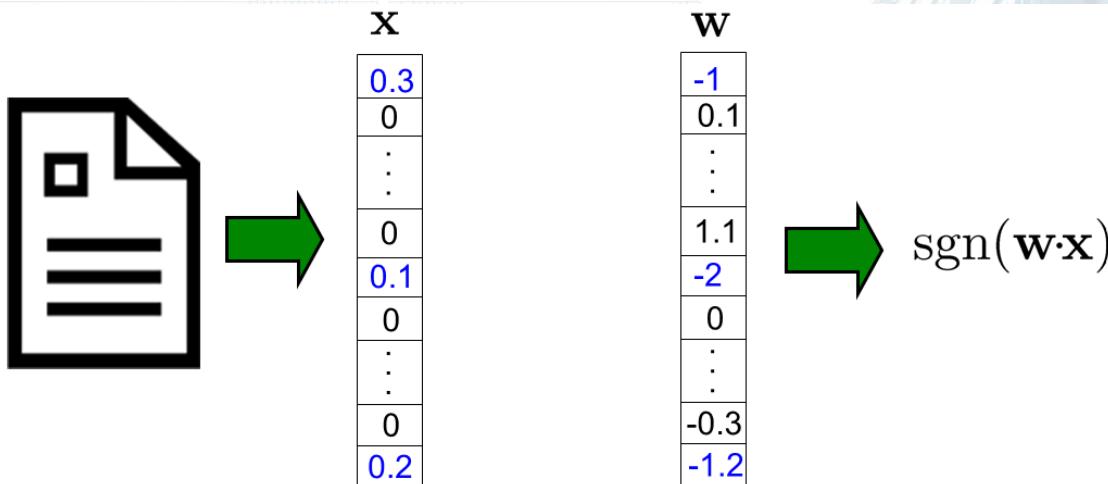
- Motivation
- Related Work
- Approach Overview
- Methodology
- Experiments
- Conclusions

Sentence-level Sentiment Classification

- Input: a sentence
- Output: sentiment polarity of the sentence
 - Positive/Negative

Sentence-level Sentiment Classification

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- Method: bag-of-words(BOW) + Classification



Drawbacks

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- BOW ignores the relationship among words and sentences.
- Useful linguistic phenomena hard to handle.
 - Negation: 我不喜欢这家酒店 (I don't like the hotel).
 - Contrast: 酒店位置好(The hotel location is good) , 但是设施糟糕 (but its facilities are poor)

How to Improve

- For relationship among words:
 - n-Gram, dependency

How to Improve

■ For relationship among words:

- n-Gram, dependency

■ For relationship among sentences:

- Discourse structure
- Compound Sentence structure

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Help

Chinese Contrast Sentences Sentiment classification

How to Improve

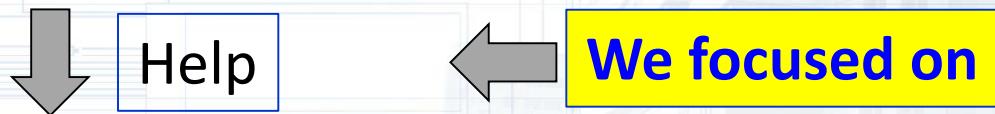
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Chinese Contrast Sentences Sentiment classification

Contrast Sentence Structure

- Two clauses in contrast sentence:
 - nuclei clause
 - satellite clause

Contrast Sentence Structure

■ Two clauses in contrast sentence:

- nuclei clause
- satellite clause

酒店位置好

(The hotel location is good)

satellite clause

但是设施糟糕

(but its facilities are poor)

nuclei clause

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Related Work

The hotel location is good, but its facilities are poor

Word-level weight

$w_1 \ w_2$

$w_3 \ w_4$

w_5

$w_6 \ w_7$

Clause-level weight

$w_{(s1)}$

$w_{s(2)}$

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- SNSS (Single Nucleus Single Satellite Method)[2,11,13] gets clause-level weights according to different clauses in contrast relation.
- Joint strategy[5]: simultaneity learns both two BOW model (satellite part and nuclei part).

We Can Do Better.....

- Q: Different connectives result in different label.
 - 酒店位置好(The hotel location is good) , 只是设施糟糕 (yet its facilities are poor)
 - 酒店位置好(The hotel location is good) , 但是设施糟糕 (but its facilities are poor)

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- A: Consider connectives not just contrast relation.

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- Q: The pipeline approach often causes error propagation.
- A: Propose a model which jointly learn weights in both clause-level and word-level together.

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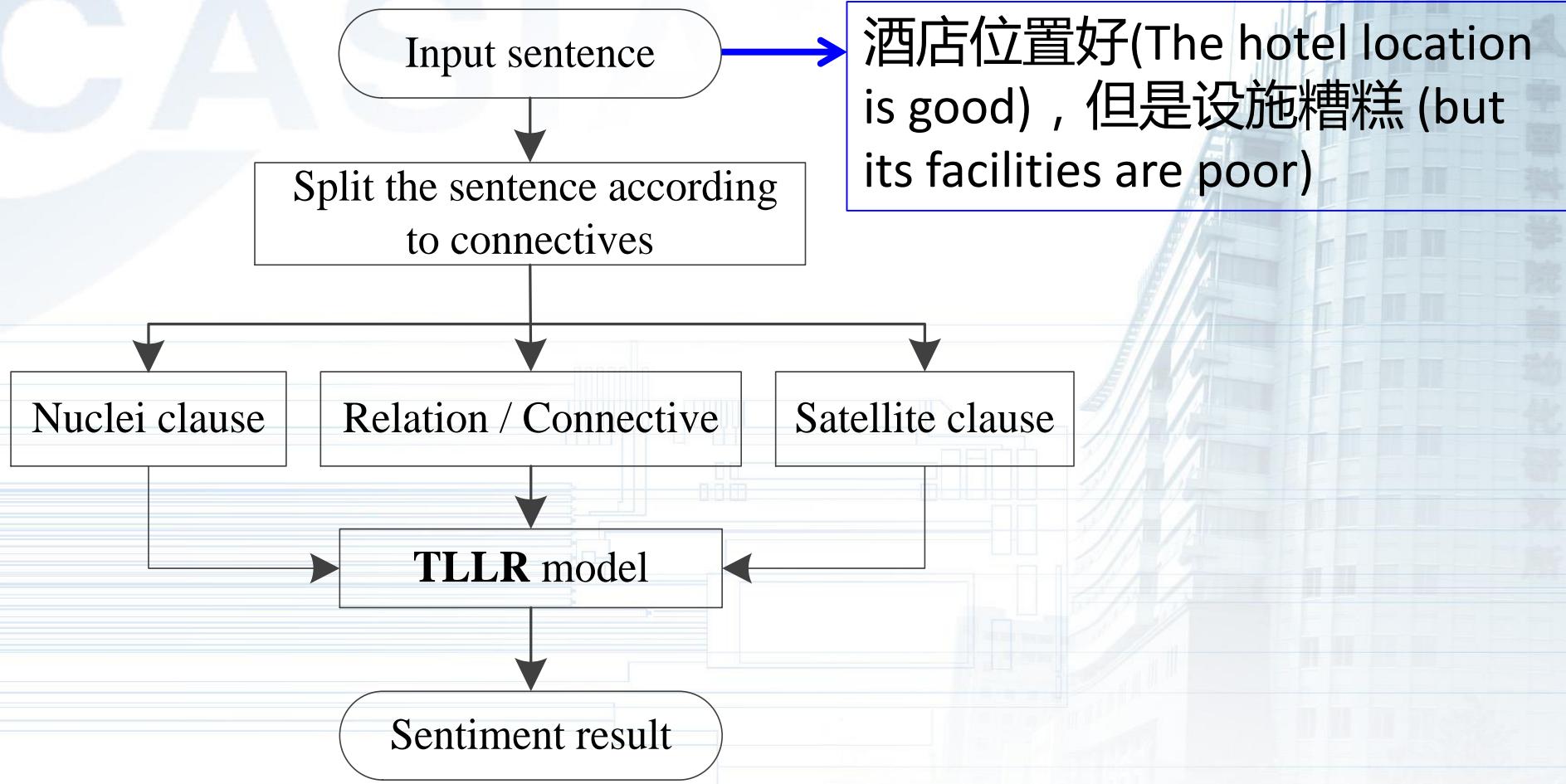
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Two-Layer Logistic Regression (TLLR) model

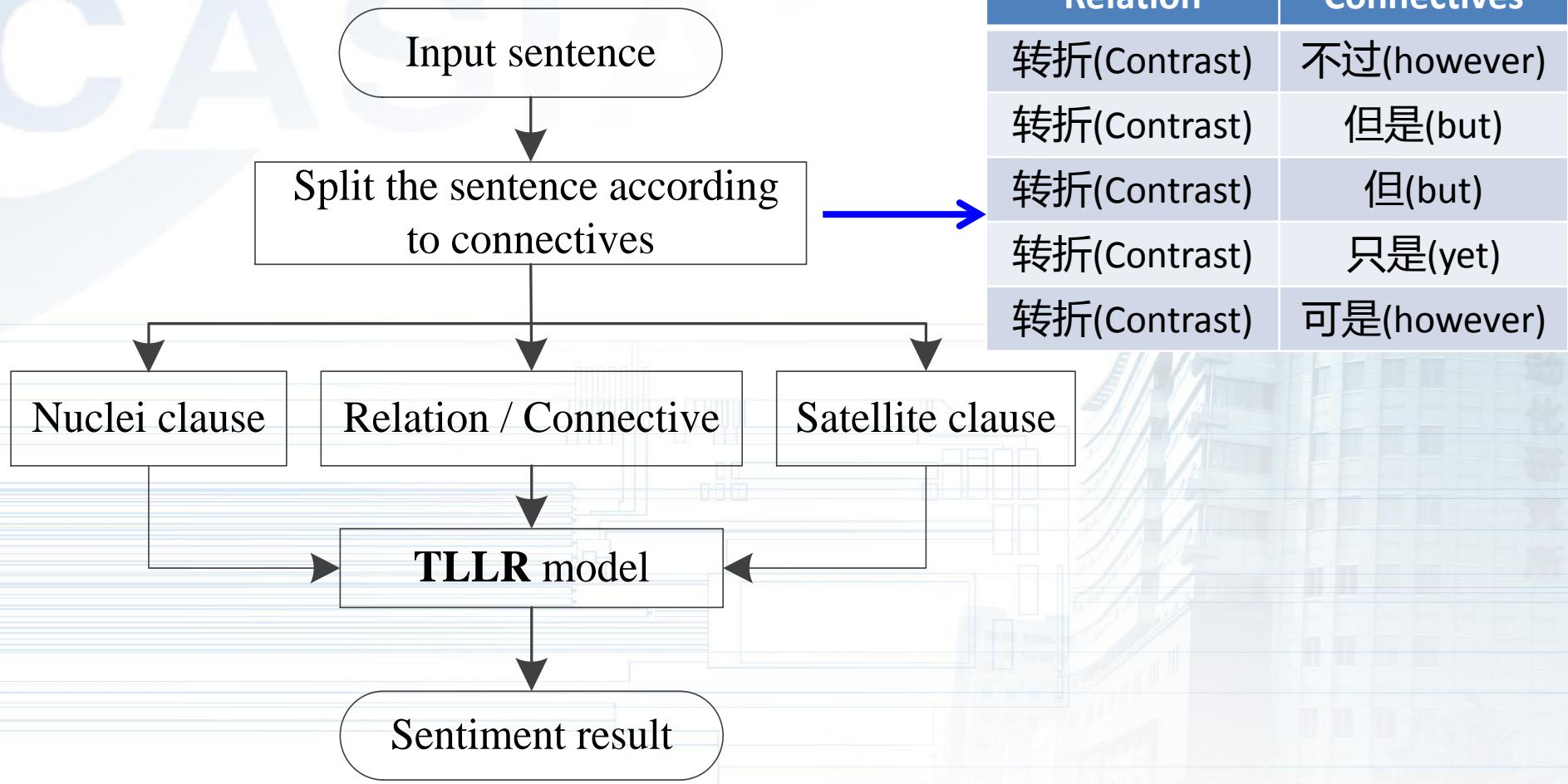
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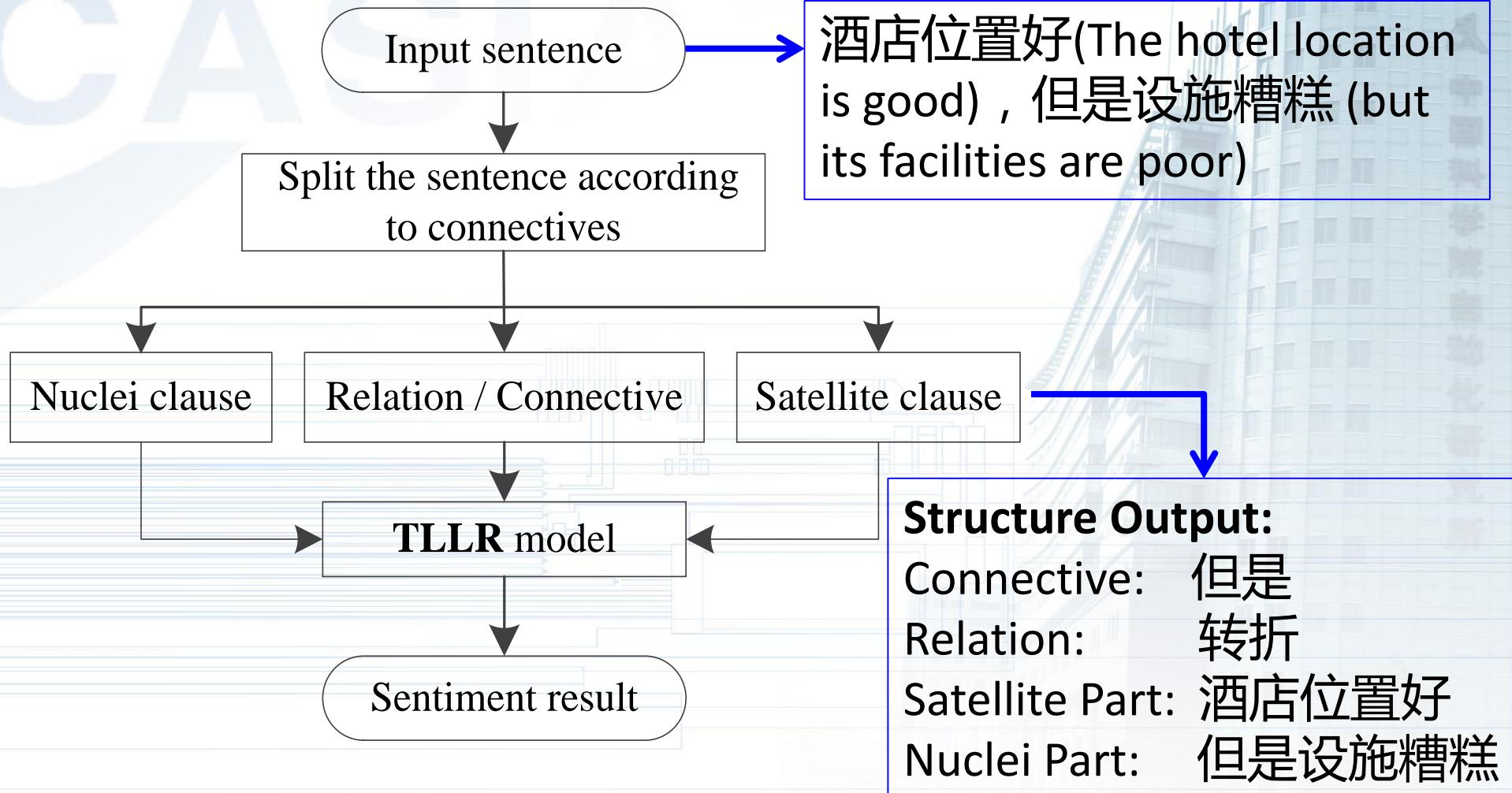
Approach Overview



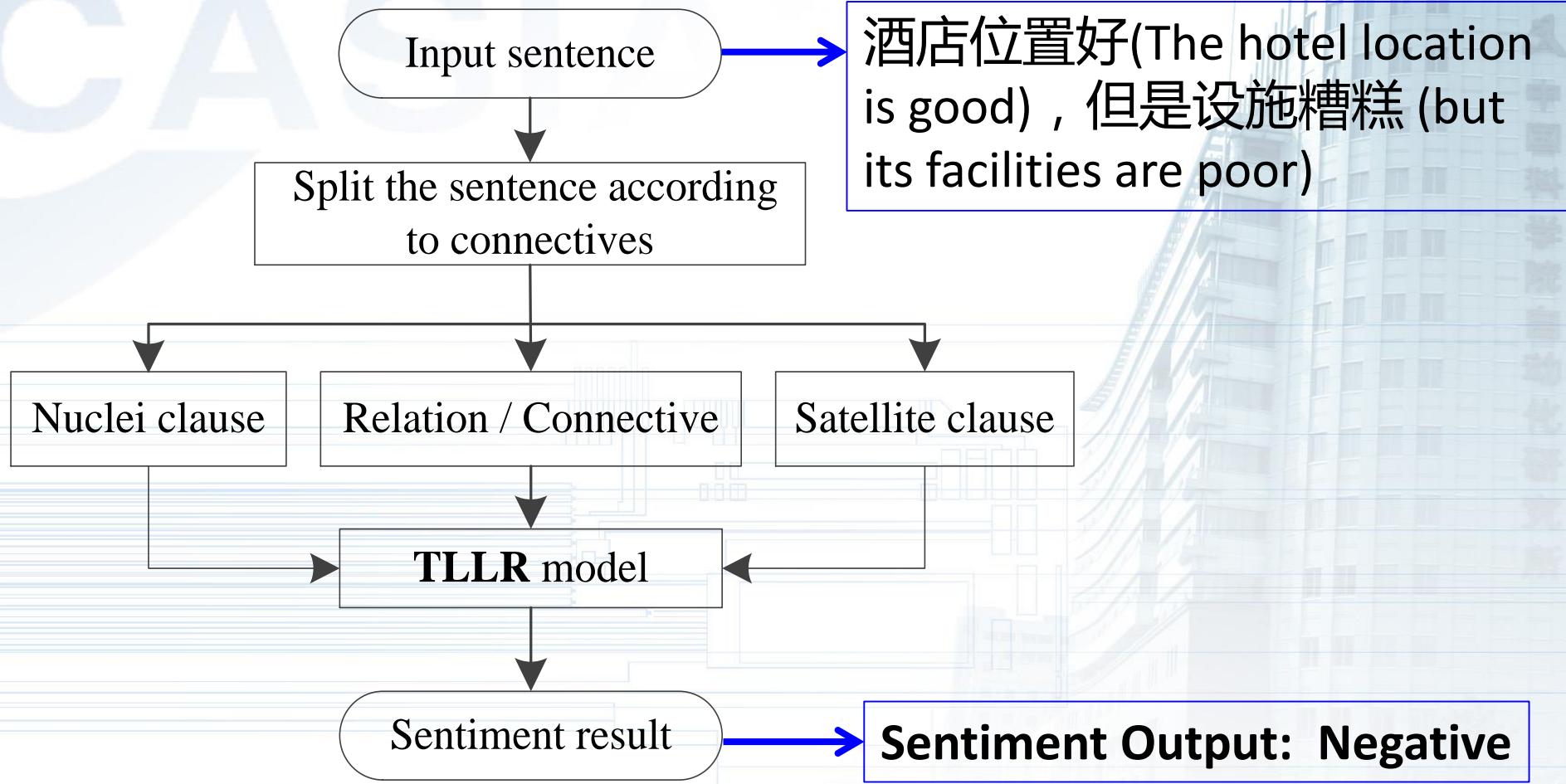
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Logistic Regression

Input Sentence: 酒店位置好(The hotel location is good) , 但是设施糟糕 (but its facilities are poor)

Logistic Regression

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Feature Vector(\vec{x}):

酒店 位置 好 , 但是 设施 糟糕

Word Weight Vector($\vec{\theta}$):

$\theta(\text{酒店}) \ \theta(\text{位置}) \ \theta(\text{但是}) \ \theta(\text{糟糕})$

Logistic Regression

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Classification:

$$P(y=1 | \vec{x}) = h(\vec{\theta} \cdot \vec{x}) = \frac{1}{1 + e^{-\vec{\theta} \cdot \vec{x}}}$$

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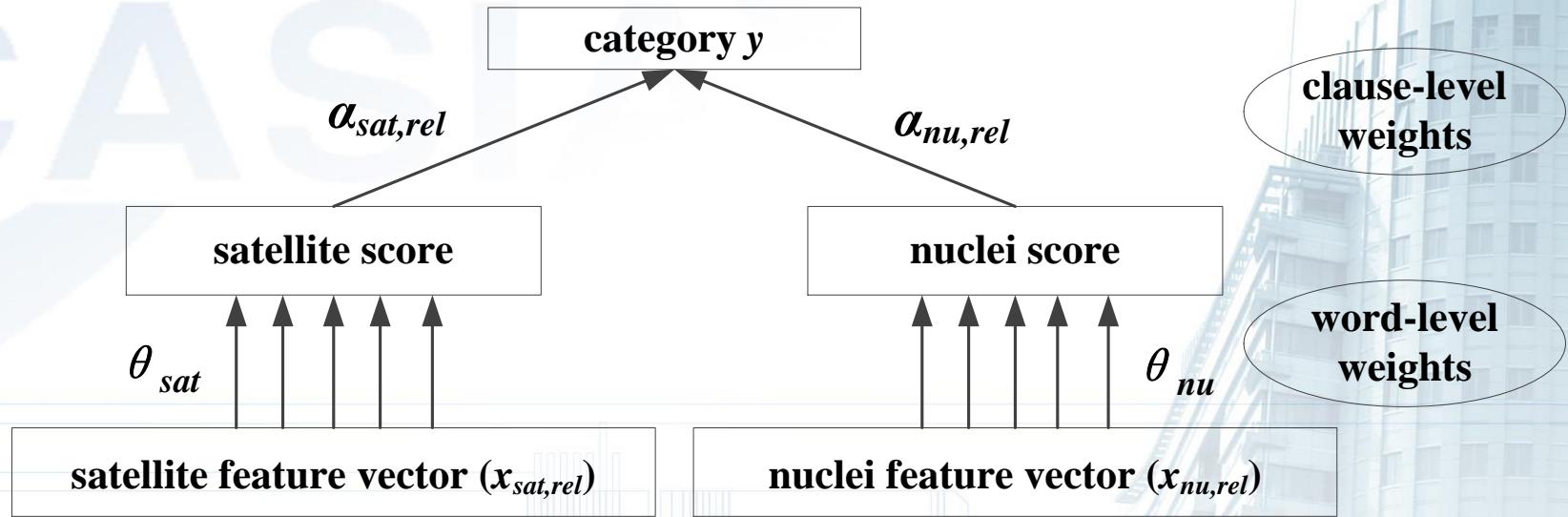
Classification:

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Loss Function:

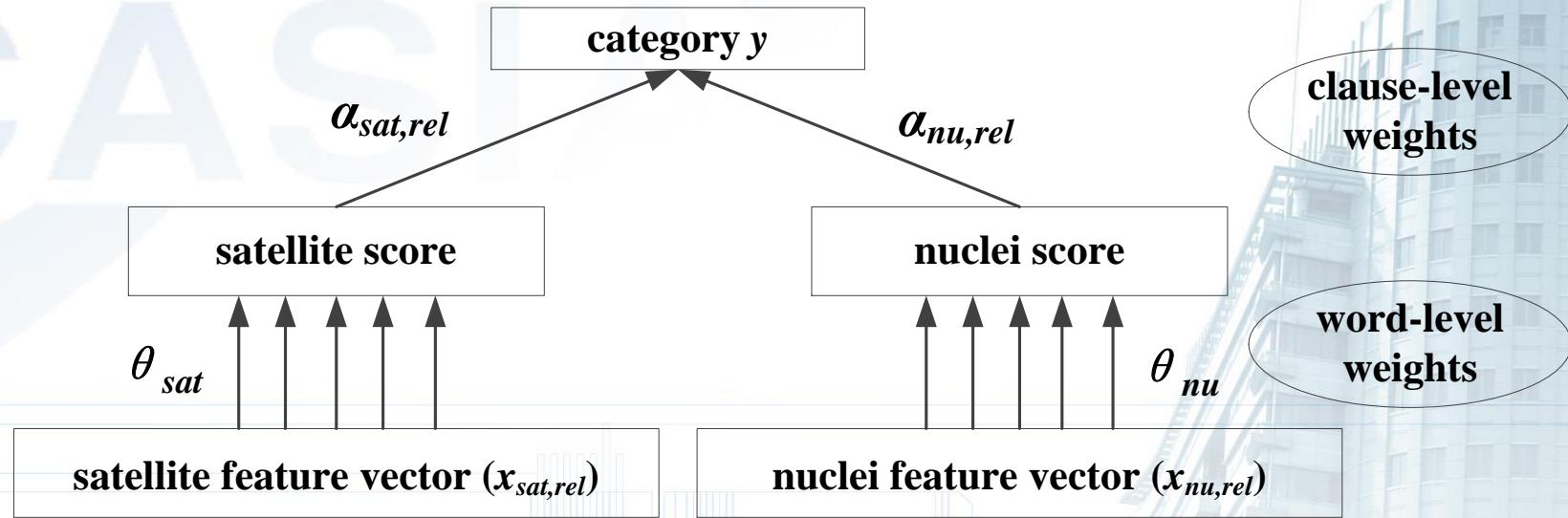
$$Cost(h(\vec{\theta} \cdot \vec{x}_k), y_k) = \begin{cases} -\log(h(\vec{\theta} \cdot \vec{x}_k)) & \text{if } y_k = 1 \\ -\log(1 - h(\vec{\theta} \cdot \vec{x}_k)) & \text{if } y_k = 0 \end{cases}$$

Two-Layer Logistic Regression



$$P(y=1 | \vec{x}) = h\left(\alpha_{sat,rel} \times (\overrightarrow{\theta_{sat}} \cdot \overrightarrow{x_{sat,rel}}) + \alpha_{nu,rel} \times (\overrightarrow{\theta_{nu}} \cdot \overrightarrow{x_{nu,rel}})\right)$$

Two-Layer Logistic Regression



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Training: Similar loss function, Similar algorithm as LR

How it works?

Input Sentence: 酒店位置好(The hotel location is good) , 但是设施糟糕 (but its facilities are poor)

How it works?

Satellite: 酒店位置好

Nuclei: 但是设施糟糕

Input Sentence: 酒店位置好(The hotel location is good) , 但是设施糟糕 (but its facilities are poor)

How it works?

θ_{sat} : $\theta(\text{酒店}) \quad \theta(\text{位置})$

$x_{sat,rel}$: 酒店 位置 好

Satellite: 酒店位置好

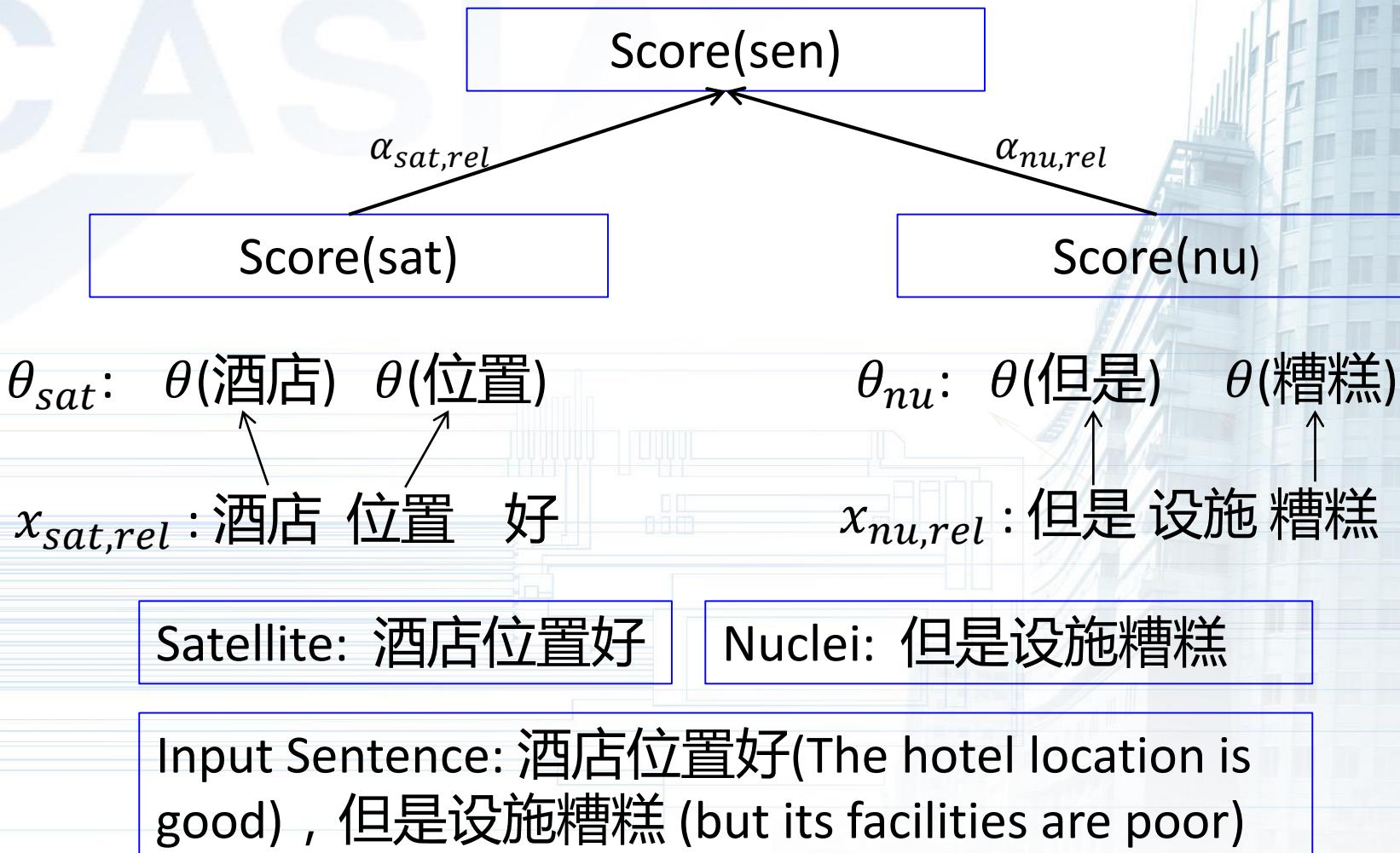
θ_{nu} : $\theta(\text{但是}) \quad \theta(\text{糟糕})$

$x_{nu,rel}$: 但是 设施 糟糕

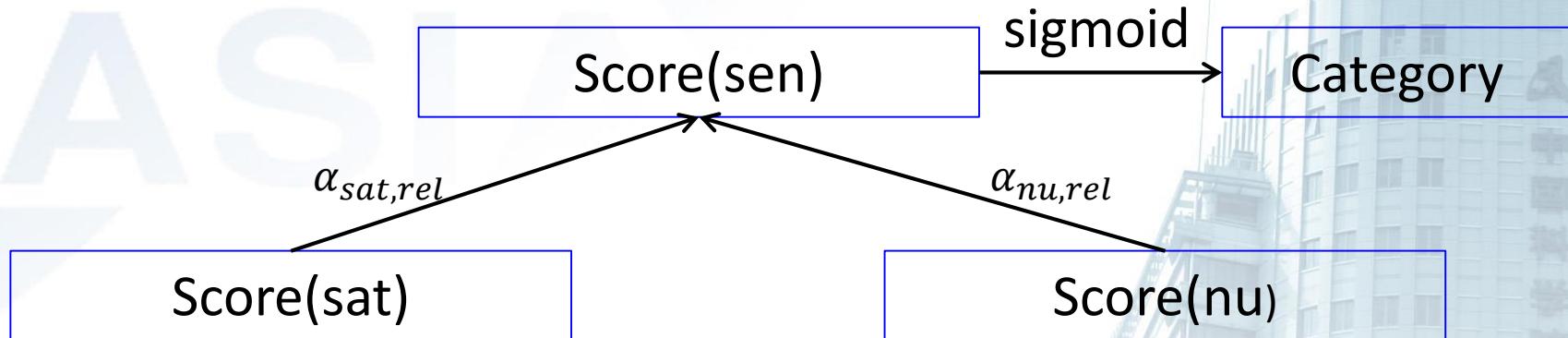
Nuclei: 但是设施糟糕

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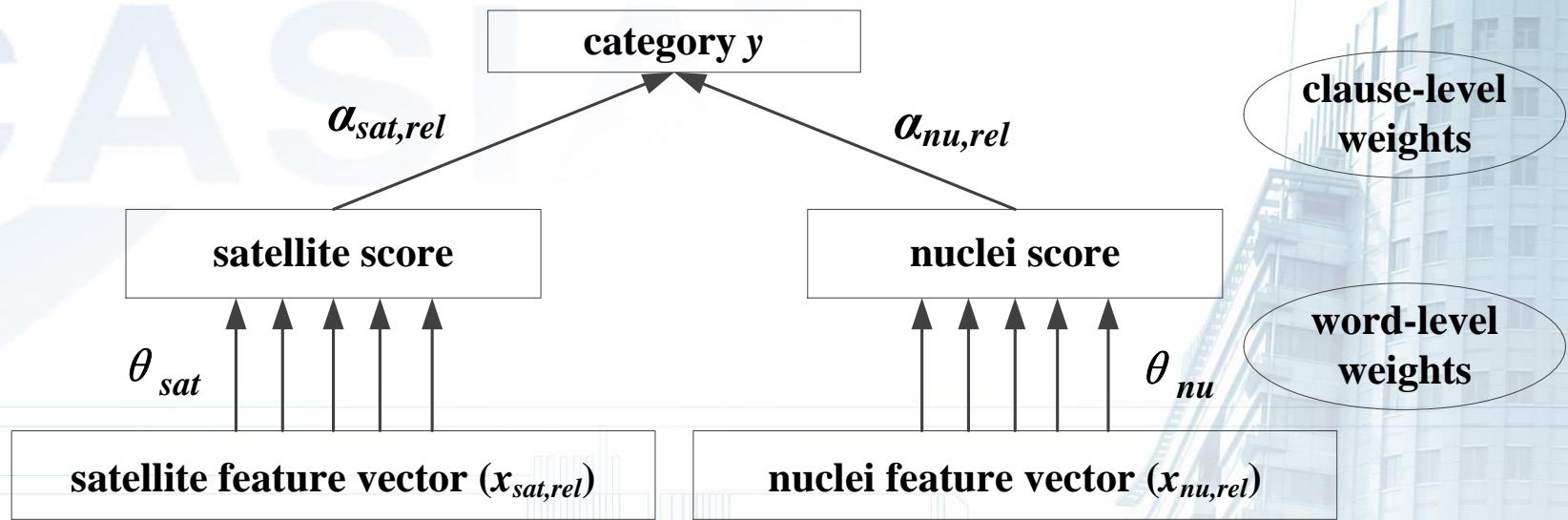
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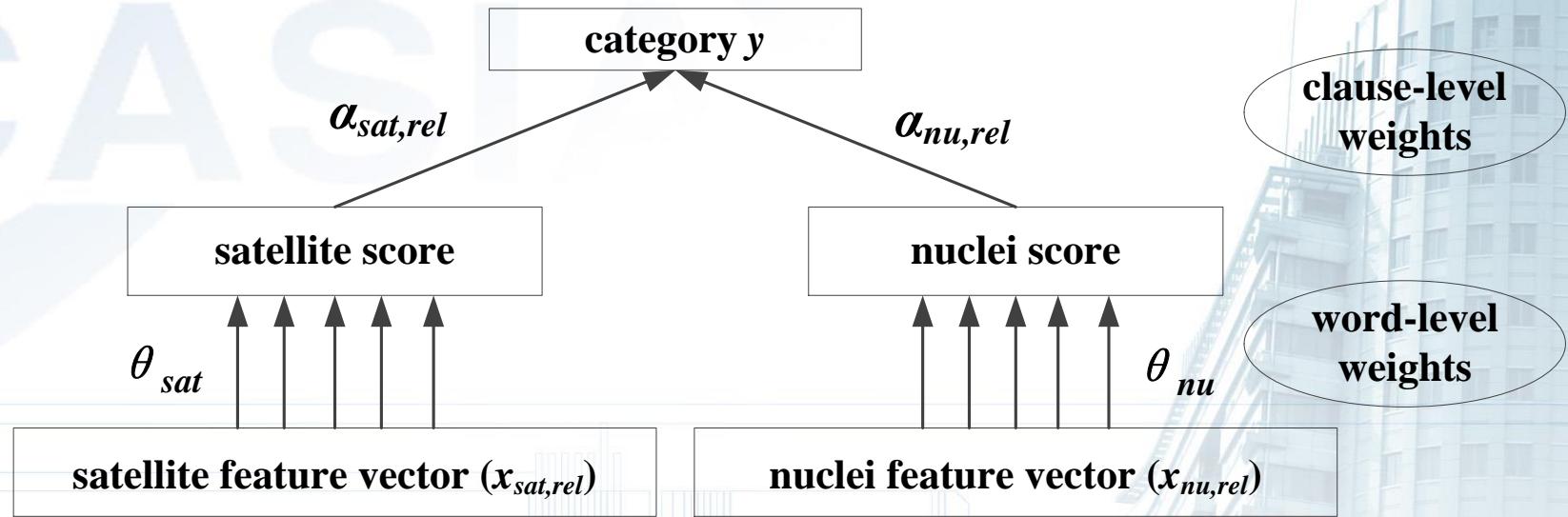
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Parameters



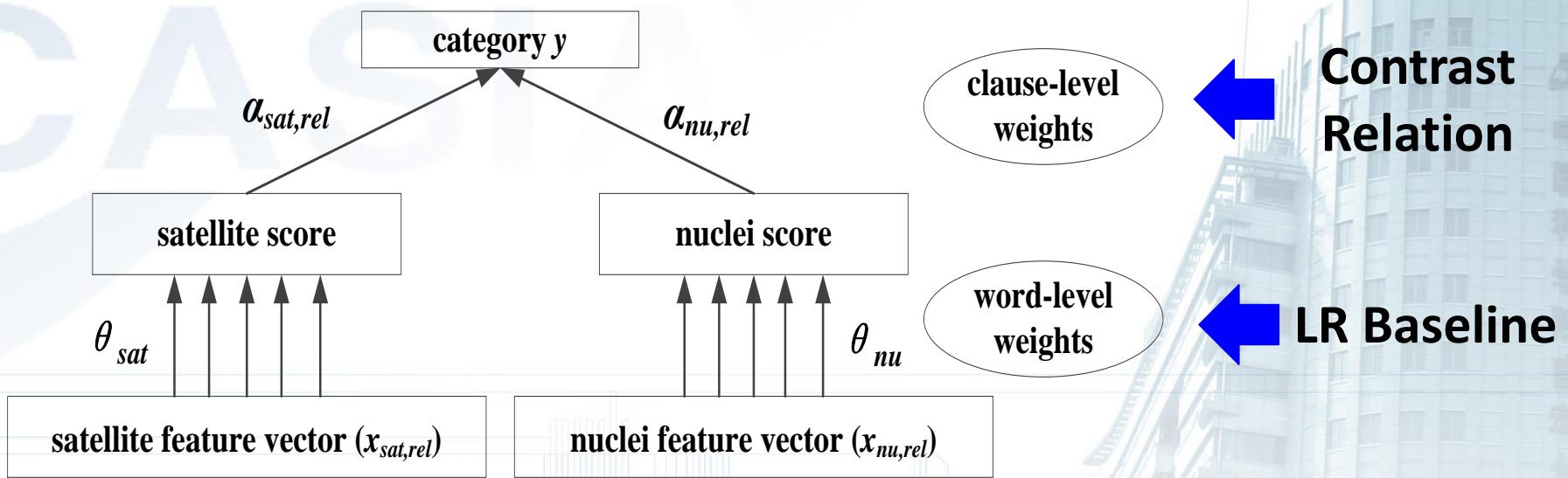
■ sat: satellite part, nu: nuclei part

Parameters



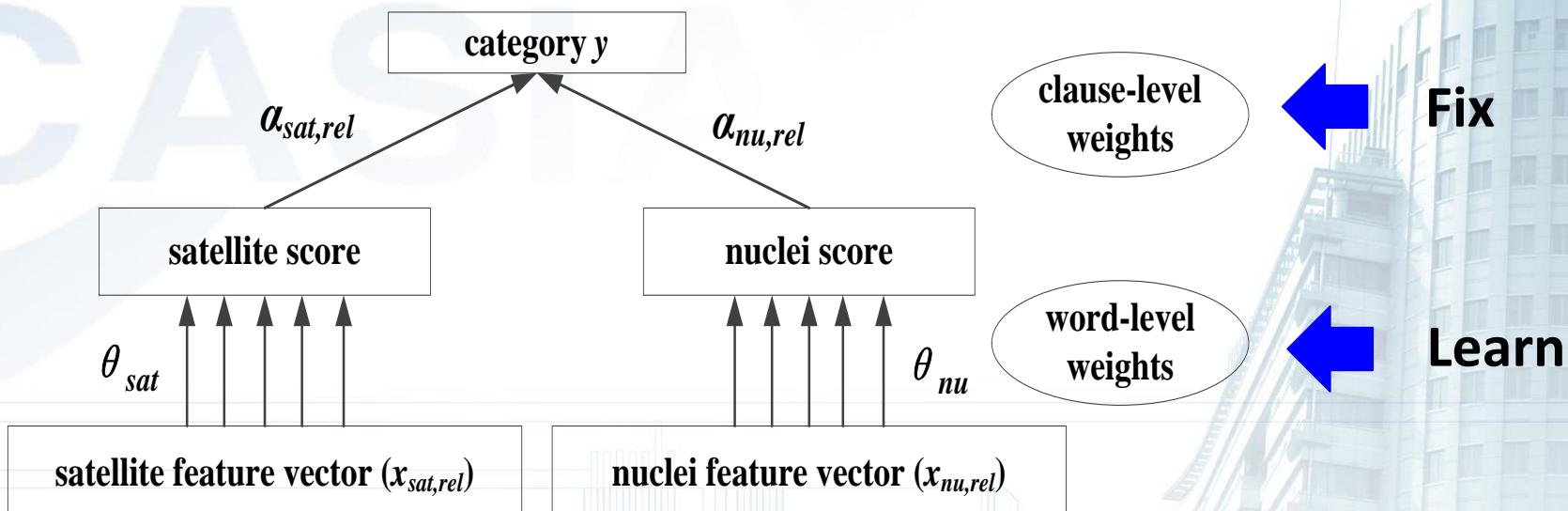
- sat: satellite part, nu: nuclei part
- rel: relation or connectives
 - Relation: 转折(contrast)
 - Connectives: 但是(but), 只是(yet)

Compared With Related Work



- SNSS: learn different clauses weight according to relation.

Compared With Related Work



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- Joint strategy: simultaneity learns both two BOW model (satellite part and nuclei part).

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Distribution of Connectives

■ Contrast sentences:

- We get 693,125 sentences from Jing Dong.
- Using contrast connectives, we get 41,629 contrast sentences, accounting for 6% in all sentences.

Experiment Dataset

- 2,000 contrast sentences as our experiment dataset:
 - Positive: 1,000
 - Negative: 1,000

Experiment Setting

- Model:
 - Baseline: SVM and LR

Experiment Setting

■ Model:

□ **Baseline:** SVM and LR

□ Other Models:

- ◆ SNSS (Single Nucleus Single Satellite Method), we get clause-level weights according to different clauses in contrast relation.
- ◆ JS (joint strategy), the joint strategy used in [5].

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□ Other Models:

- ◆ SNSS (Single Nucleus Single Satellite Method), we get clause-level weights according to different clauses in contrast relation.
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□ **Our Model:** we get the results of TLLR model.

Experiment Result

Systems	5-Fold Cross Validation Results (%)					
	1st	2nd	3rd	4th	5th	Average
SVM	86.00	86.00	83.00	85.00	85.50	85.10
LR	86.75	86.75	83.00	87.00	86.75	86.05
SNSS	86.25	88.00	83.50	86.00	86.25	86.00
JS	87.50	85.75	85.25	85.75	86.25	86.10
TLLR	86.58	87.70	84.95	86.73	87.73	86.74

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■ LR as our baseline system

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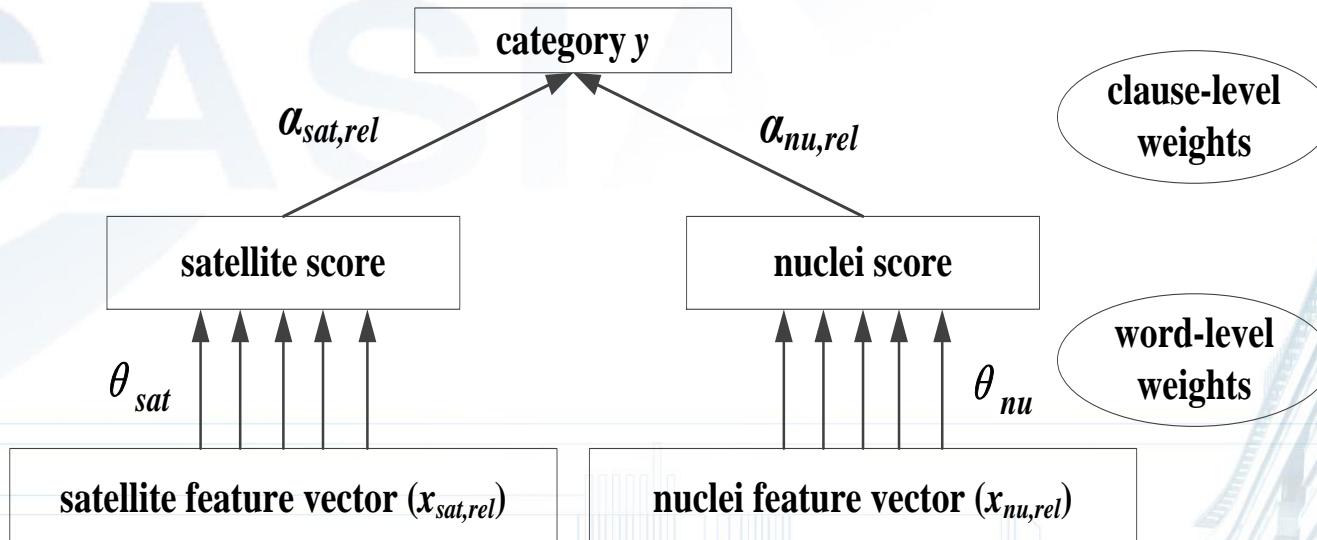
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- Comparable Related Work: Word weight learn from sentence may not be suitable for clause.

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- LR as our baseline system
- Comparable Related Work: Word weight learn from sentence may not be suitable for clause.
- Learn word weight and clause weight together is better

Parameter Analysis

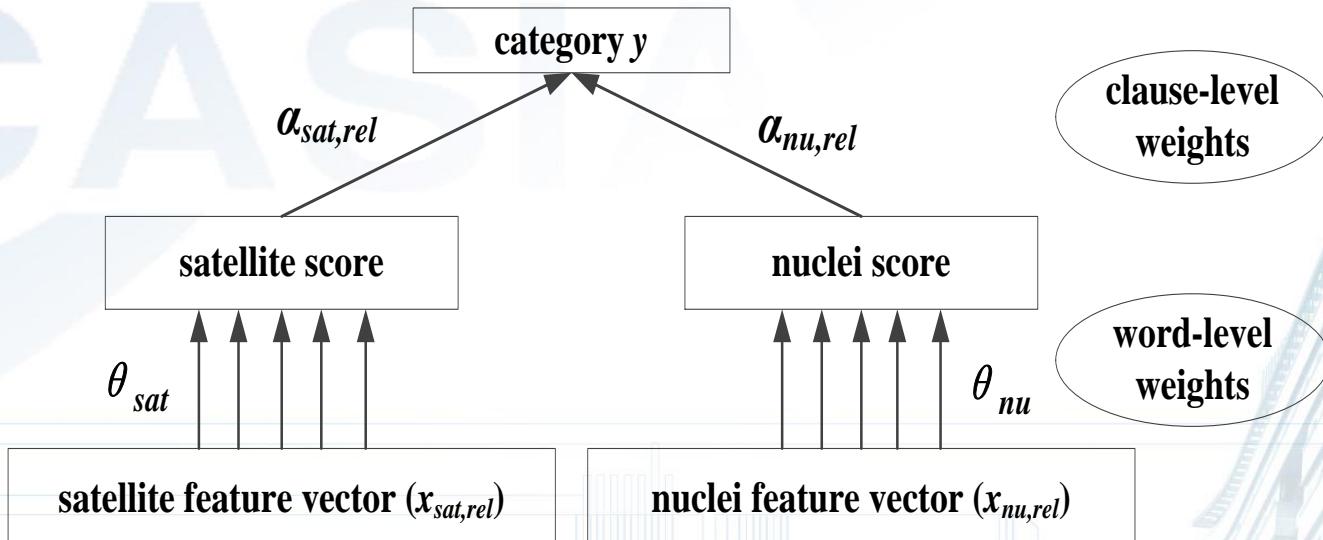


Contrast Relation

LR Baseline

Parameter 1: FixRelation

Parameter Analysis



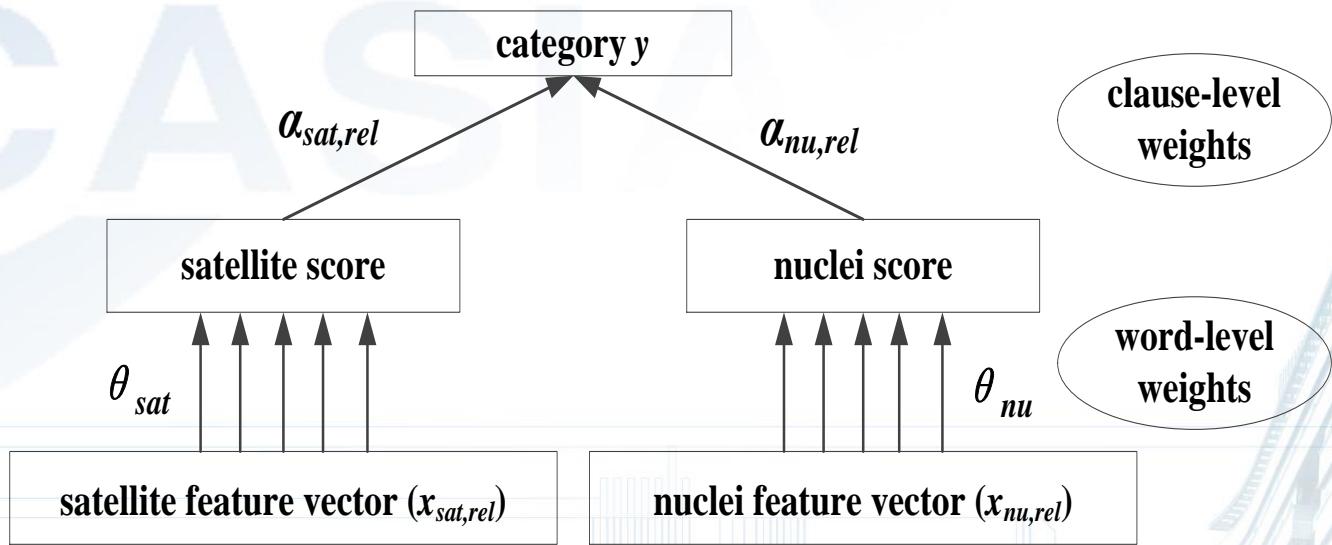
Contrast
Connective

LR Baseline

Parameter 1: FixRelation

Parameter 2: FixConnective

Parameter Analysis



Contrast
Relation

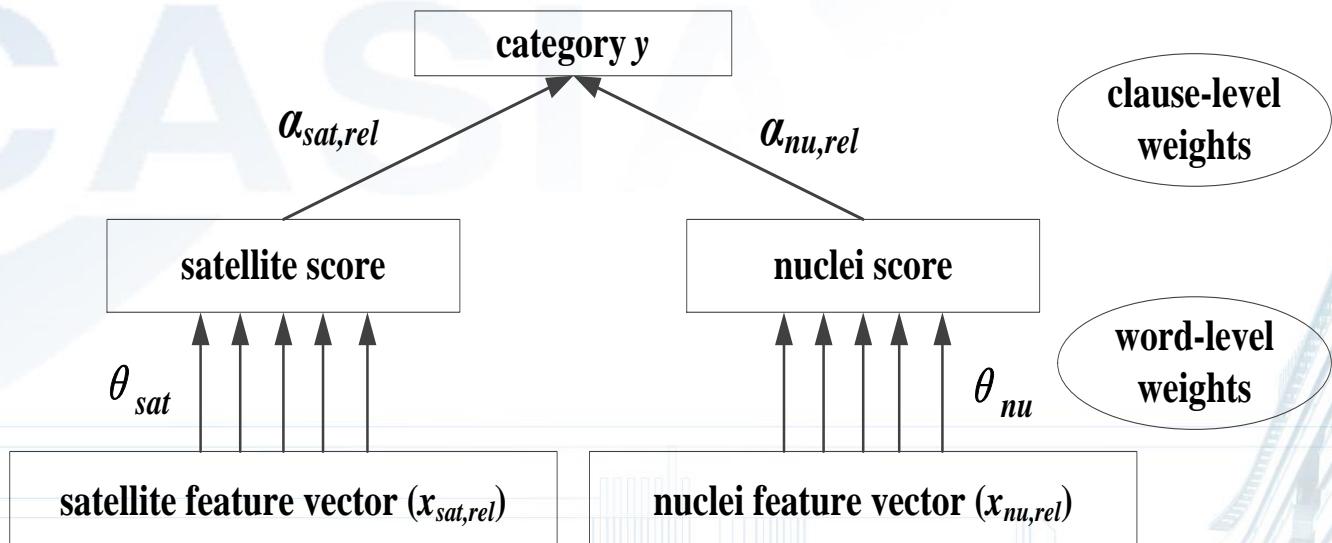
Learn

Parameter 1: FixRelation

Parameter 2: FixConnective

Parameter 3: DiffRelation

Parameter Analysis



Contrast
Connective

Learn

- Parameter 1: FixRelation**
- Parameter 2: FixConnective**
- Parameter 3: DiffRelation**
- Parameter 4: DiffConnective**

Parameter Analysis Result

Systems	Average (5-fold)
FixRelation	86.00%
FixConnective	86.45%
DiffRelation	86.40%
DiffConnective	86.74%

- “Connective” is better than “Relation”

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- “Connective” is better than “Relation”
- “Diff” is better than “Fix”

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- “Connective” is better than “Relation”
- “Diff” is better than “Fix”
- “Diff” + “Connective” is the best

Clause-level Weight Analysis

Model	Type	Satellite	Nuclei
FixRelation	转折 Contrast	0.48	0.52
FixConnective	不过 however	0.6	0.4
	但 but	0.46	0.54
	但是 but	0.41	0.59
	只是 yet	0.56	0.44
	可是 however	0.41	0.59
DiffRelation	转折 Contrast	0.45	0.55
DiffConnective	不过 however	0.58	0.42
	但 but	0.42	0.58
	但是 but	0.36	0.64
	只是 yet	0.55	0.45
	可是 however	0.34	0.66

转折:
Nuclei > Satellite

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不过 只是:

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Conclusions

- TLLR model is proposed.
 - TLLR model considers clause-level weights with connectives, not just relations.
 - TLLR model can learn word weights and clause-level weights together.
- Future Work:
 - Consider other relations.
 - Deduce the overall polarity from the polarity of each aspect.

References

- [2] Bas Heerschap, Frank Goossen, Alexander Hogenboom, Flavius Frasincar, Uzay Kaymak, and Franciska de Jong. 2011. Polarity analysis of texts using discourse structure. *In Proceedings of the ACM international conference on Information and knowledge management(CIKM)*. pages 1061–1070.
- [5] Shoushan Li and Chu-Ren Huang. 2009. Sentiment Classification Considering Negation and Contrast Transition. *In Proceedings of the Pacific Asia Conference on Language, Information, and Computation (PACLIC)*.
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- [13] Fei Wang, Yunfang Wu, and Likun Qiu. 2012. Exploiting Discourse Relations for Sentiment Analysis. *In Proceeding of the Intenerational Conference of Computational Linguistics(COLING)*. pages 1311–1319.

Thanks!

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Contrast Connectives	Sentence Number	Sentence Proportion (%)
不过(however)	14,869	35.72
但是(but)	11,919	28.63
但(but)	9,553	22.95
只是(yet)	3,047	7.32
可是(however)	2,241	5.38
All	41,629	100