Incorporating Singletons and Mention-based Features in Coreference Resolution via Multi-task Learning for Better Generalization

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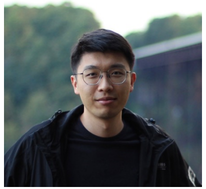
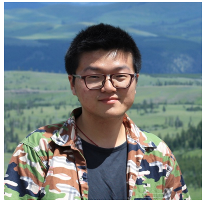

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Coreference Resolution and Mentions: An Example

*“ **I** voted for **Mary** because **Mary** was most aligned with **Jack’s** values”, **John** said.*

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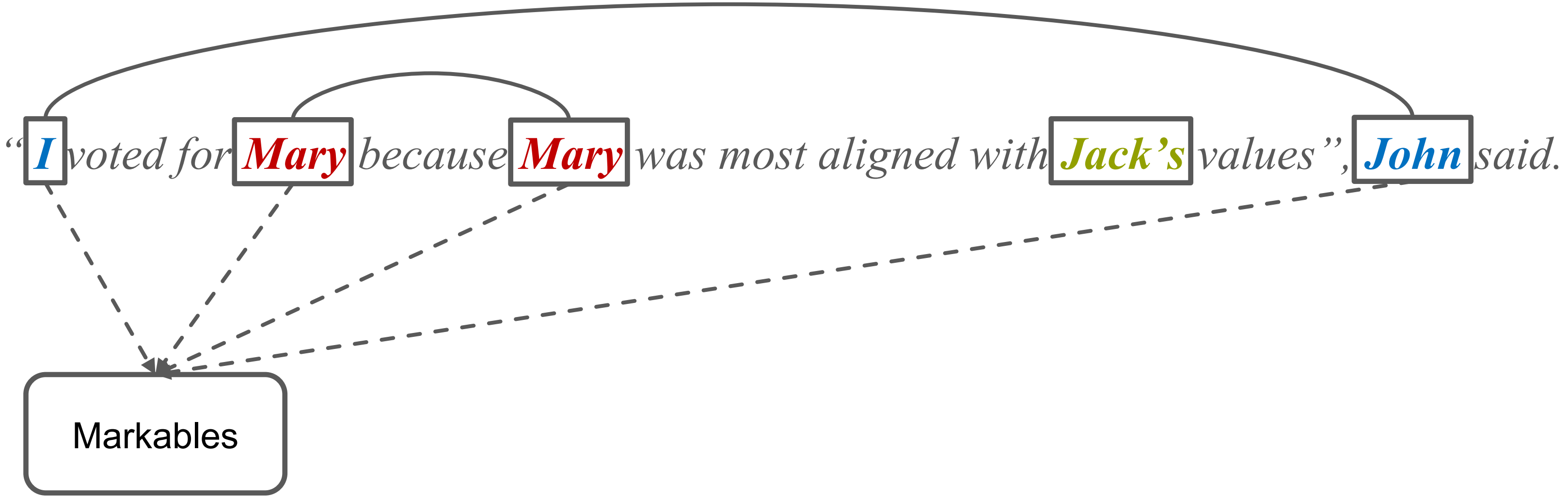

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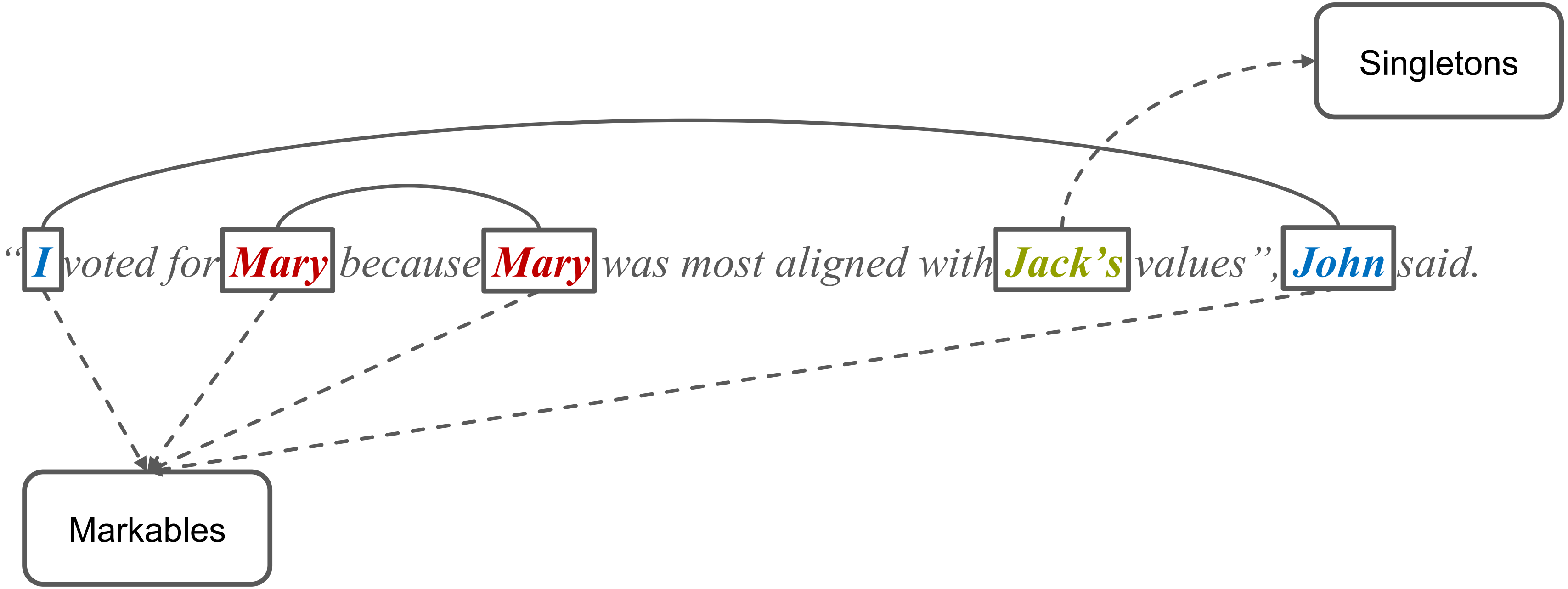
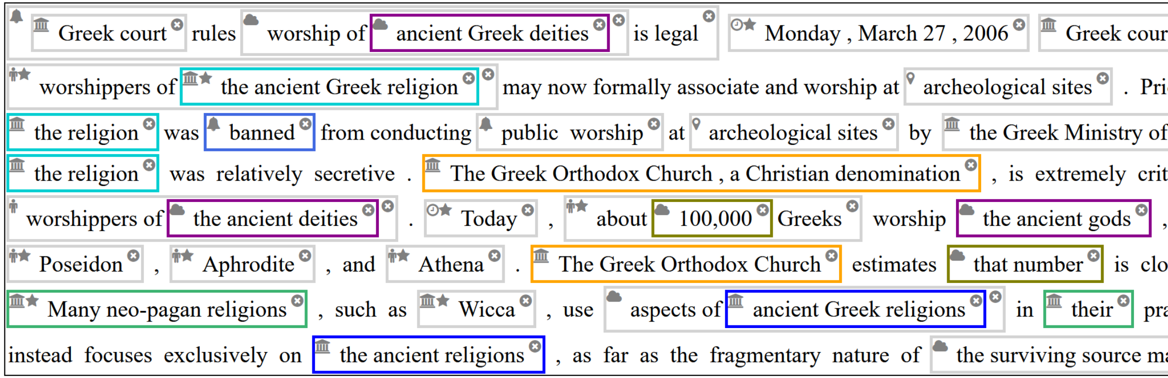


Why Are Singletons Important?

- How humans understand discourse from a theoretical perspective (Grosz et al., 1995)
  - Singletons constitute mentioned entities (i.e. clusters of size 1)

- Represent true negatives in cluster linking (Kübler and Zhekova, 2011)

However…



- Dataset - OntoNotes
  - Lack singleton annotation

- Coreference Models

  End-to-end (Lee et al., 2017, Lee et al., 2018, Joshi et al., 2020, Dobrovolskii, 2021, etc.) & ***Seq2seq*** (Bohnet et al., 2023)
  - Models cannot differentiate singleton spans from non-referring or random/meaningless spans, thus penalizing these two types equally
  - Do not align with linguistic theories on how humans resolve the task

Features Other Than Singletons?

*“ **I** voted for **Mary** because **Mary** was most aligned with **Jack’s** values”, **John** said.*

Jack’s

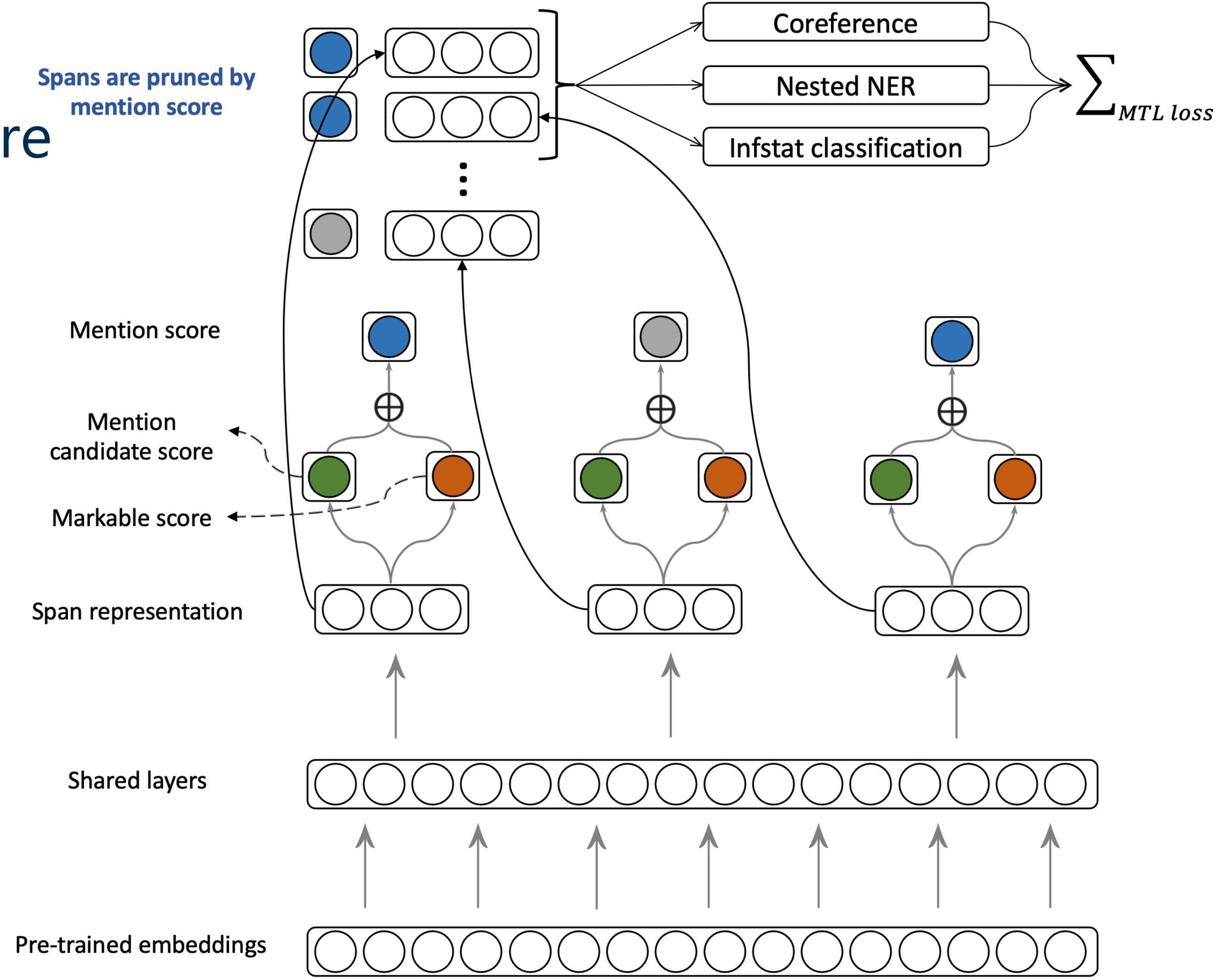
Entity type: ***person***

Information status: ***new***

Datasets

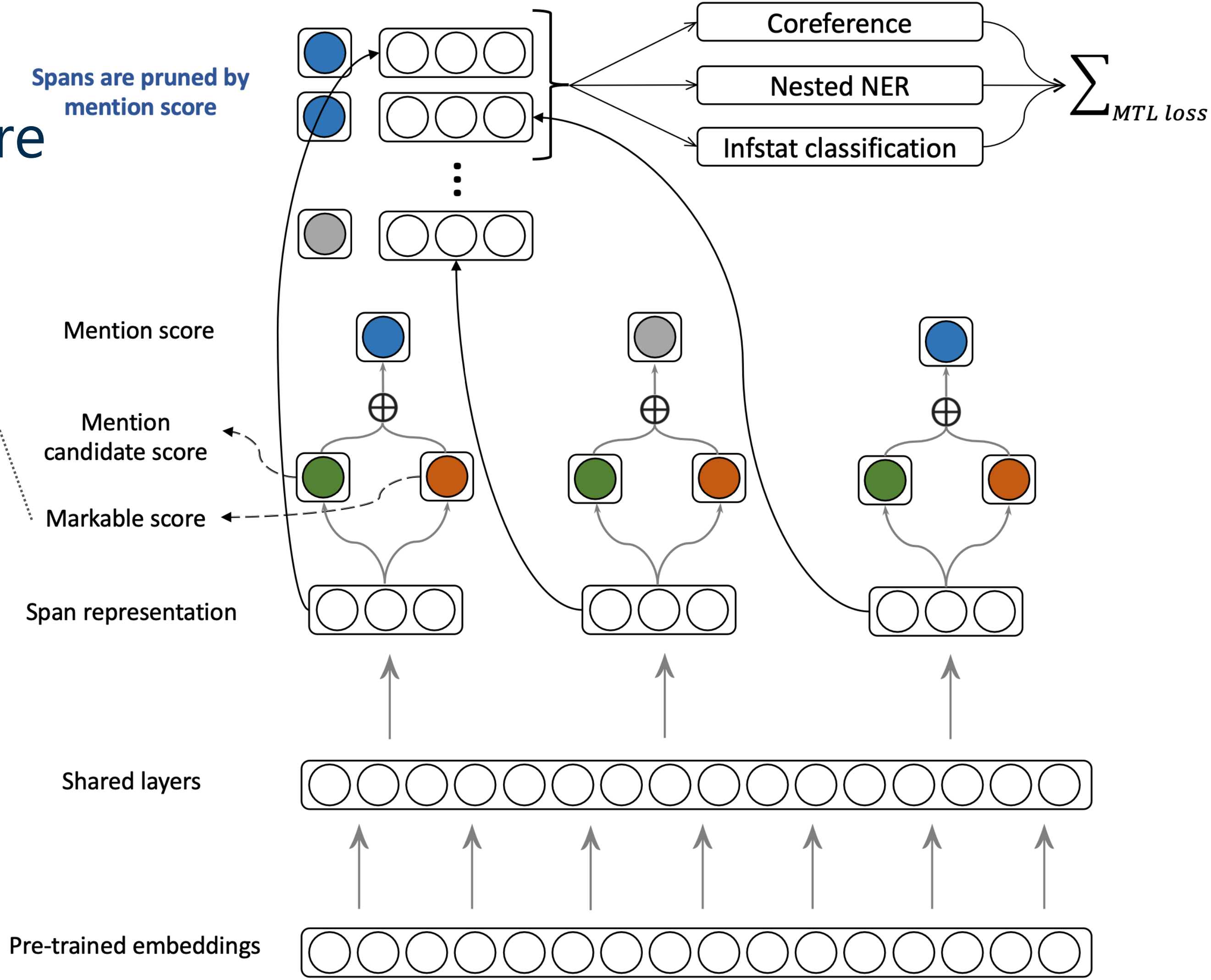
- In-domain
  - OntoGUM (Zhu et al., 2021): dataset has multi-layer annotations of
    - Singletons & Markables
    - Mention-based annotations
      - Entity types (abstract, animal, event, object, organization, person, place, plant, substance, time)
      - Information status (new, given:active, given:inactive, accessible:inferrable, accessible:commonground, accessible:aggregate)
    - Coreference relations following OntoNotes guidelines
- Out-of-domain
  - OntoNotes V5.0 (Weischedel et al., 2011; Pradhan et al., 2013)
  - WikiCoref (Ghaddar and Langlais, 2016)

Model Architecture



Model Architecture

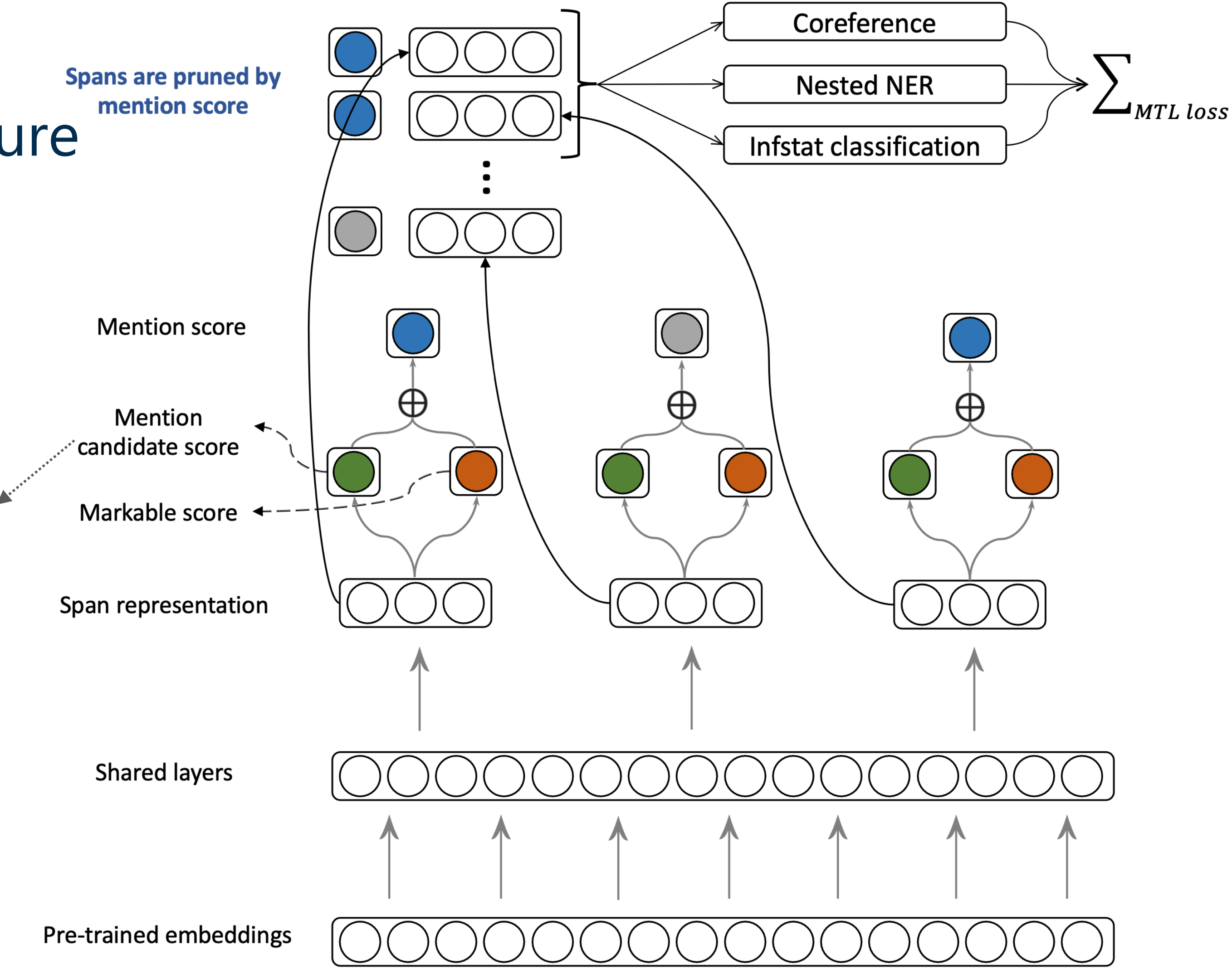
Markable score
How likely a span is coreferred in the document?



Model Architecture

Markable score
How likely a span is coreferred in the document?

Mention candidate score
How likely a span is a mention?



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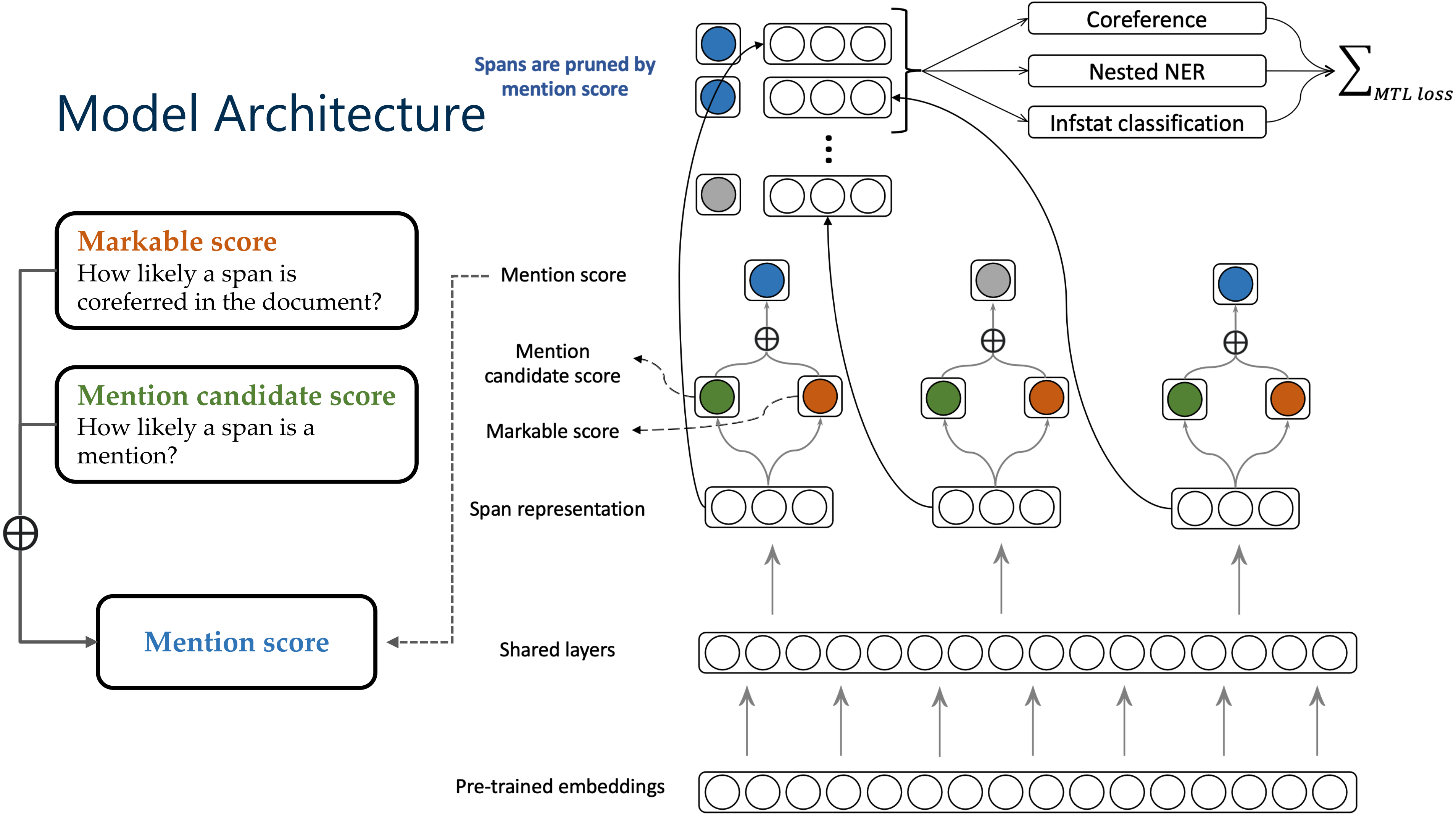
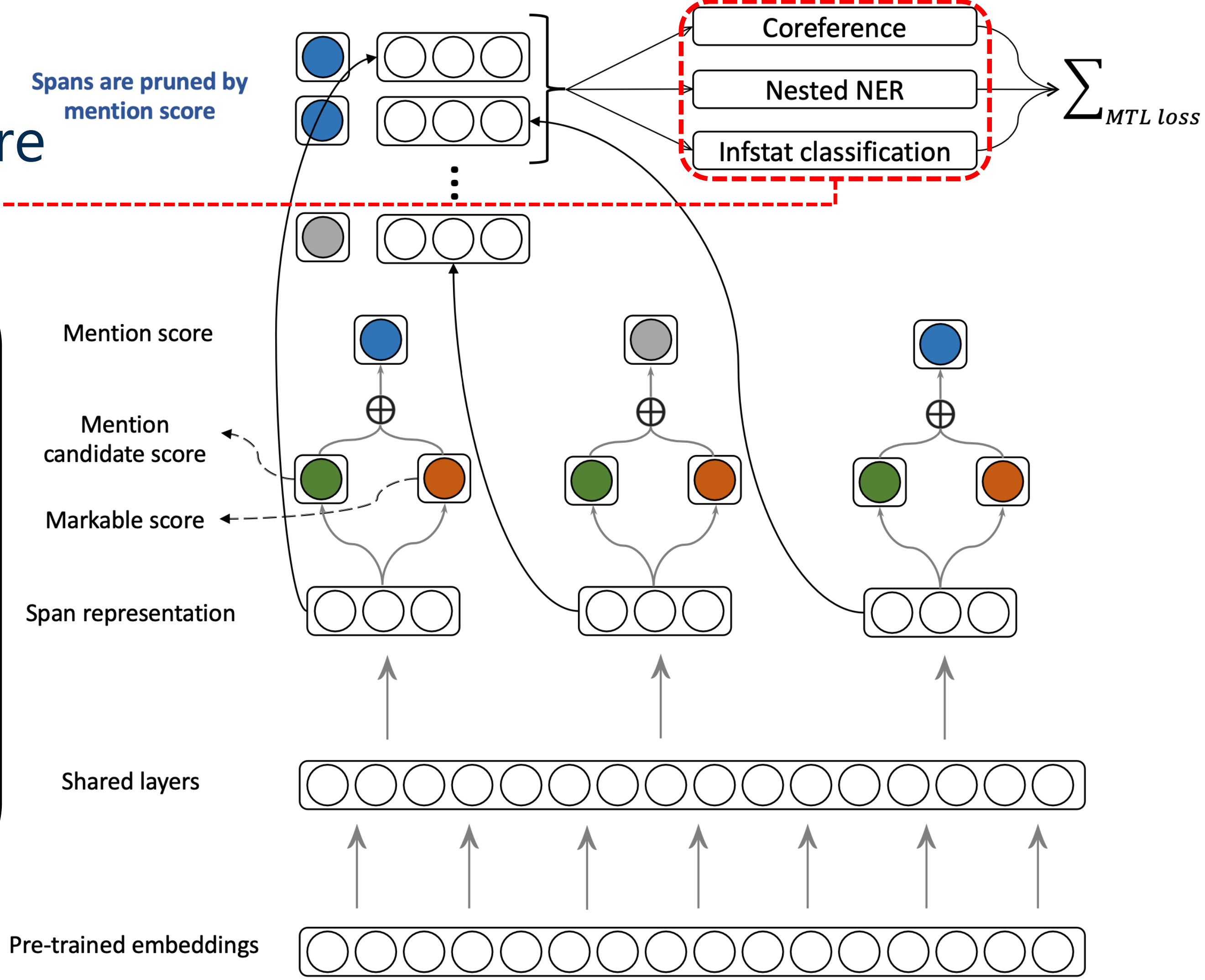


Model Architecture

- **Coreference linking**

- **Entity type recognition:**
Assign a non-pruned span one of the ten types

- **Infstat classification:**
Assign a non-pruned span one of the six classes



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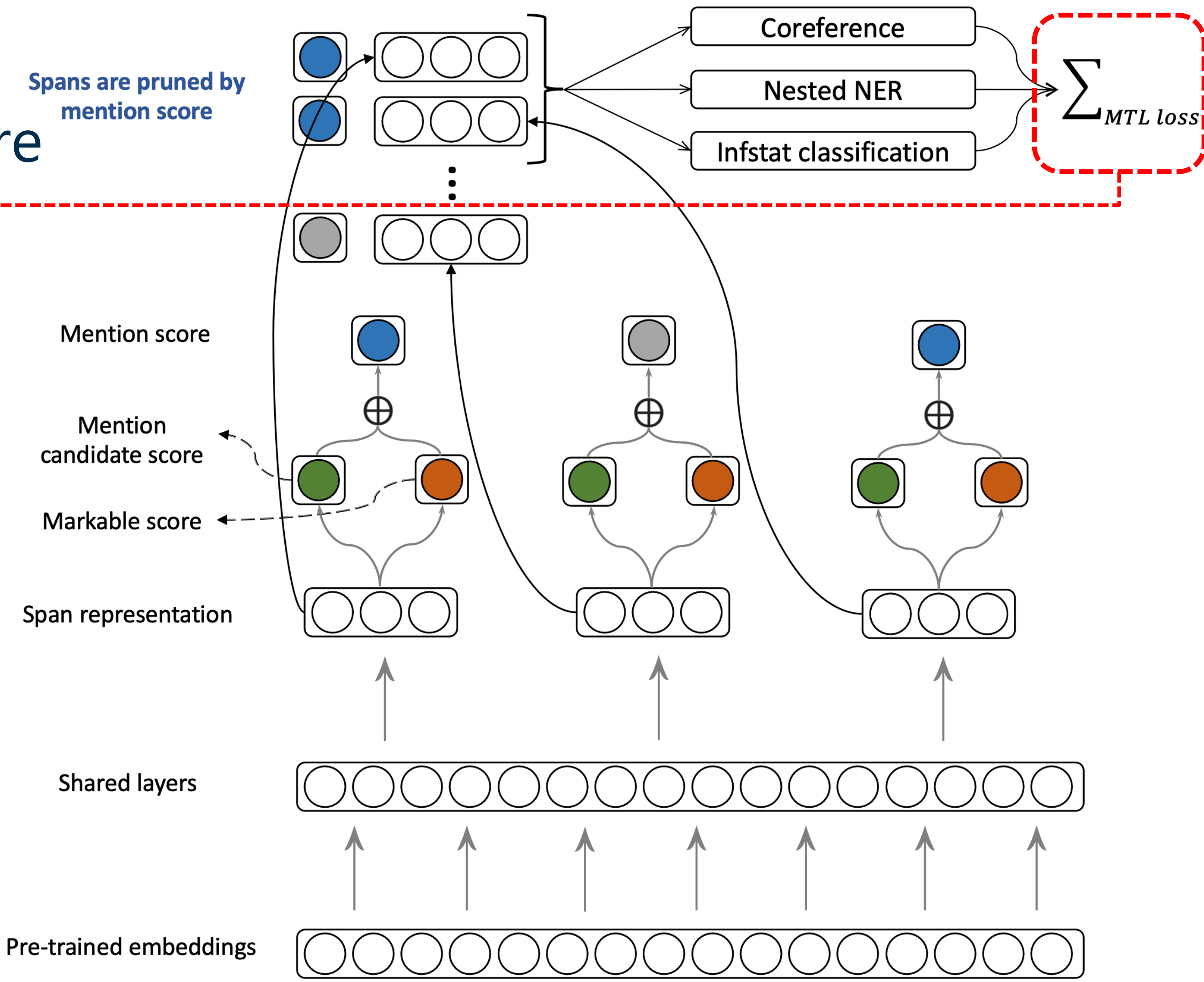

- Task weights for MTL loss

$$\mathcal{L}_{total} = \sum_{t=1}^{T} \omega_t * \mathcal{L}_t$$

Hyperparameter tuning to find the best weights

Experiments & Results

	Markble Detection			MUC			B^3			$CEAF_{\phi 4}$			Avg. F1
	P	R	F1	P	R	F1	P	R	F1	P	R	F1	
In-domain - ONTOGUM													
Joshi et al. (2019)	**91.0**	71.9	80.3	**83.3**	69.7	75.9	70.8	59.2	64.5	70.5	45.8	55.5	65.5
MTL (sg)	90.2	75.0	**81.9**	82.7	72.8	77.4	70.4	63.1	66.5	71.5	49.2	58.3	67.6
MTL (sg+ent)	90.0	**75.1**	**81.9**	82.8	**72.9**	**77.6**	**71.2**	**63.6**	**67.2**	**71.9**	**50.2**	**59.1**	**68.2**
MTL (sg+ent+infs.)	90.0	75.0	81.8	82.1	72.3	76.9	70.0	62.3	65.9	70.0	48.6	57.3	66.9
Out-of-domain - ONTONOTES													
Joshi et al. (2019)	**83.9**	76.9	80.3	**77.6**	72.7	75.1	66.9	60.6	63.6	**64.3**	54.5	59.0	65.9
MTL (sg+ent)	82.2	**80.2**	**81.2**	77.0	**76.1**	**76.5**	**67.1**	**64.0**	**65.5**	63.6	**59.5**	**61.5**	**67.8**
Out-of-domain - WIKICOREF													
Joshi et al. (2019)	79.9	58.8	67.7	73.7	60.1	66.2	66.4	43.4	52.4	56.6	31.6	40.5	53.0
MTL (sg+ent)	**80.4**	**60.0**	**68.7**	**74.5**	**61.8**	**67.5**	**67.8**	**45.3**	**54.4**	**59.0**	**33.0**	**42.4**	**55.6**

Table 1: Comparison between Joshi et al. (2019) and our model on test sets of both in-domain (OntoGUM 8.0) and out-of-domain datasets (OntoNotes and WikiCoref). The overall F1 score is the average of F1s from three evaluation metrics MUC, B^3, and $CEAF_{\phi 4}$. All models are trained on OntoGUM.

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Best setting: MTL-sg+ent

Improve the baseline model by <u>2.7</u> points **<u>in domain</u>**

Experiments & Results

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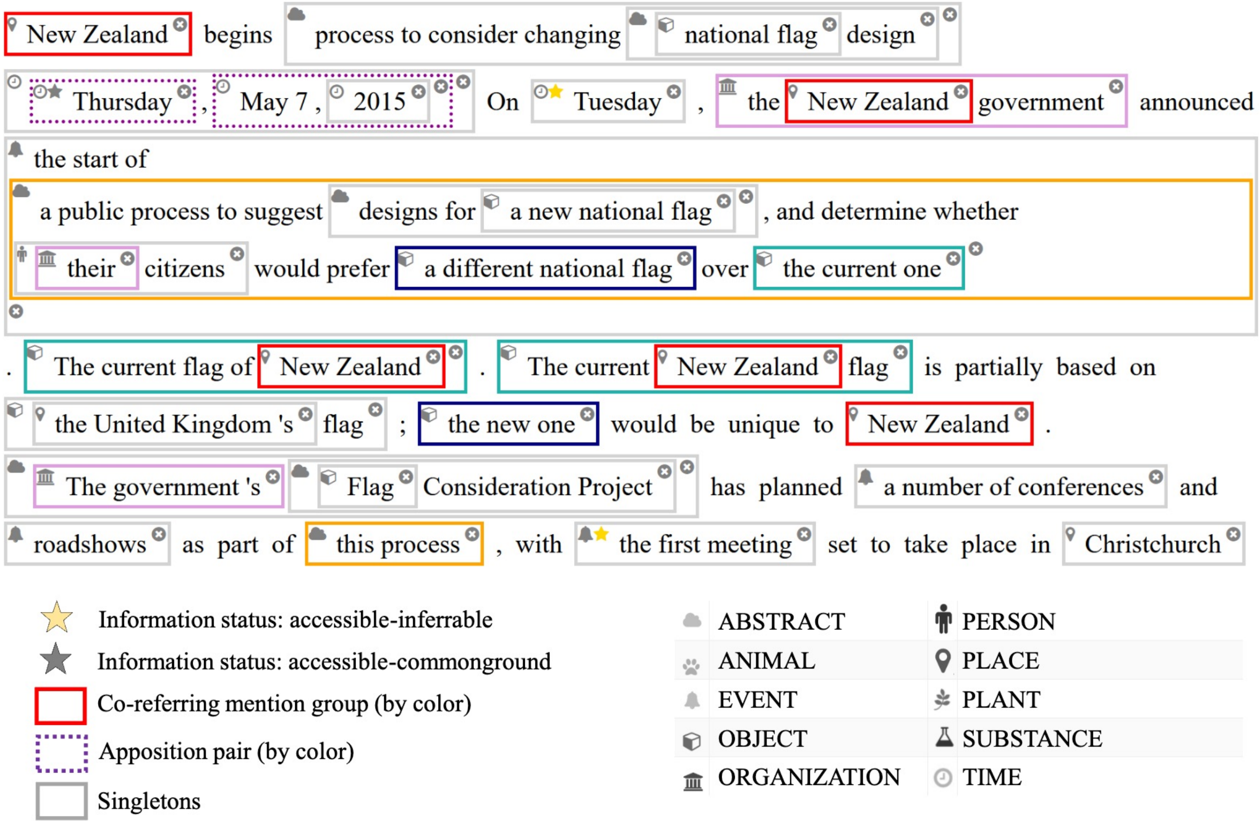
Best setting: MTL-sg+ent

Improve the baseline model by **2.3** points **out domain** by average

Expected Outputs

Joint predictions of

- Mention spans
- Coreference relations
- Entity types
- Information status



Error Analysis

Error type	mtl errors		e2e errors	
Pronouns				
- 1st & 2nd person pronouns	6	3.6%	12	5.0%
- 3rd person pronouns	20	12.1%	68	28.3%
Definiteness				
- Definite nouns	63	38.2%	98	40.8%
- Indefinite nouns	13	7.9%	13	5.4%
Proper nouns	23	14.0%	19	7.9%
Others	40	24.2%	30	12.5%
Total	165	100.0%	240	100.0%

Table 3: Number and percentage of errors by class that are produced by e2e but avoided by the MTL model (e2e errors) and produced by the MTL model but resolved by the e2e model (mtl errors).

Analysis following Lu and Ng (2020)

Error types	MTL vs baseline
- Pronouns	26 vs 80
- Definiteness	76 vs 111
- Proper nouns	23 vs 19
- Others	40 vs 30

Conclusion

- We propose a MTL based neural coreference model with constrained mention detection, which jointly learns several mention-based tasks
- Achieve new SOTA performance on the OntoGUM test set
- Demonstrate better generalization on two OOD datasets
- Release our code at: https://github.com/yilunzhu/coref-mtl

Appendix A: Ablation Study

	Avg. F1	Δ
Base model	67.0	
w/ singleton detection (=sg)	68.3	+1.3
w/ sg + entity type (=ent)	68.7	+0.4
w/ sg + ent + information status	67.8	-0.9

Table 2: Comparison of various tasks included in the coreference model on the OntoGUM development data.

Singletons (sg) and entity types (et)	+1.7
Sg, ent, and information status	+0.8

Appendix B: Example Errors

GOLD: by [brackets]
ERROR: in colored text

- Example 1-3
Entity-type recognition contributes to resolution by avoiding type mismatches

- Example 4-5
Mention detection identifies missing mentions in the baseline model or improves boundary recognition

Entity type errors	
1	he did represent [the school]$_1$ during the very first Eton v [Harrow]$_1$ cricket match
2	Who cut [the grass]$_1$? Marlena did [it]$_2$. Marlena did [it]$_2$ a long time ago, but [it]$_1$ hasn't been watered. [It]$_1$'s dying.
3	I made [noises]$_1$ with my heels but [they]$_1$ were too loud so I stopped.
Singleton errors	
4	The main reason attributed for the pollution of Athens is because the city is enclosed by mountains in [a basin which does not let the smog leave]$_1$ ... have greatly contributed to better atmospheric conditions in [the basin]$_1$.
5	This means that if [the govt]$_1$ decided to print 1 quadrillion dollars in the span of a week ... we 're loaning [the US govt]$_1$ the very money it prints

Table 4: A qualitative analysis of OntoGUM dev errors that appear in the e2e model but are avoided by our MTL model. MTL predictions (gold) are represented by [brackets]$_x$. E2e predictions (errors) are highlighted in colored text and each color in an example denotes a coreference cluster.