Gendered Pronoun Resolution

Dhruv Patel (14528) Prateek Sachan (15754)

Computer Science and Automation, Indian Institute of Science

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Impressed by her beauty, her warrior skills, and the fact that she was able to locate him, she is promoted to a position similar to that later held by her half-sister, Talia. As a right hand associate, she accompanies him during his adventures. Ra's is so impressed with her abilities, he even allows Nyssa to use his Lazarus Pits. Like **her** sister **Talia**, **Nyssa** eventually becomes disenchanted with Ra's genocidal plans to "cleanse the Earth", and disassociates herself from her father sometime in the early 20th century.

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- Introduced as Kaggle competition by Google AI

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  James asked **Robert** *for a favor, but* **he** *refused.*
  James *asked Robert for a favor, but* **he** *was refused.*

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As a side effect Ramsey Snow will become Ramsey Wick. In most cases this is not a problem.

Method

- If both candidate A and candidate B has less than four words and neither of them contains characters from ",(*)"
  - If pronoun is **he**, **him** or **his**
    - Find alternative male candidate of same length as A, such that no word of old A or old B is contained in new proposal.
    - Find alternative male candidate of same length as B, such that no word of old A or old B is contained in new proposal.
  - If pronoun is **she**, **her** or **hers**
    - Find alternative female candidate of same length as A, such that no word of old A or old B is contained in new proposal.
    - Find alternative female candidate of same length as B, such that no word of old A or old B is contained in new proposal.
- if old A and old B had any common word, modify proposals to behave similarly to old candidates.
- replace old A with new A, replace old B with new B.

Example

- Tony Markham, a high school senior and the "Tall Dark Stranger" Betsy fell in love with as a freshman, who has since become a good friend not only to Betsy but the entire Ray family. Mrs. Ray, Betsy's mother. Mr. Ray, Betsy's father, who owns a shoestore. **Margaret Ray**, **Betsy**'s sister who is five years younger than she is.
- Tony Markham, a high school senior and the "Tall Dark Stranger" Alyssa fell in love with as a freshman, who has since become a good friend not only to Alyssa but the entire Jolie family. Mrs. Jolie, Alyssa's mother. Mr. Jolie, Alyssa's father, who owns a shoestore. Angelina Jolie, Alyssa's sister who is five years younger than she is.
- Tony Markham, a high school senior and the "Tall Dark Stranger" Booth fell in love with as a freshman, who has since become a good friend not only to Booth but the entire Delgado family. Mrs. Delgado, Booth's mother. Mr. Delgado, Booth's father, who owns a shoestore. Pam Delgado, Booth's sister who is five years younger than she is.

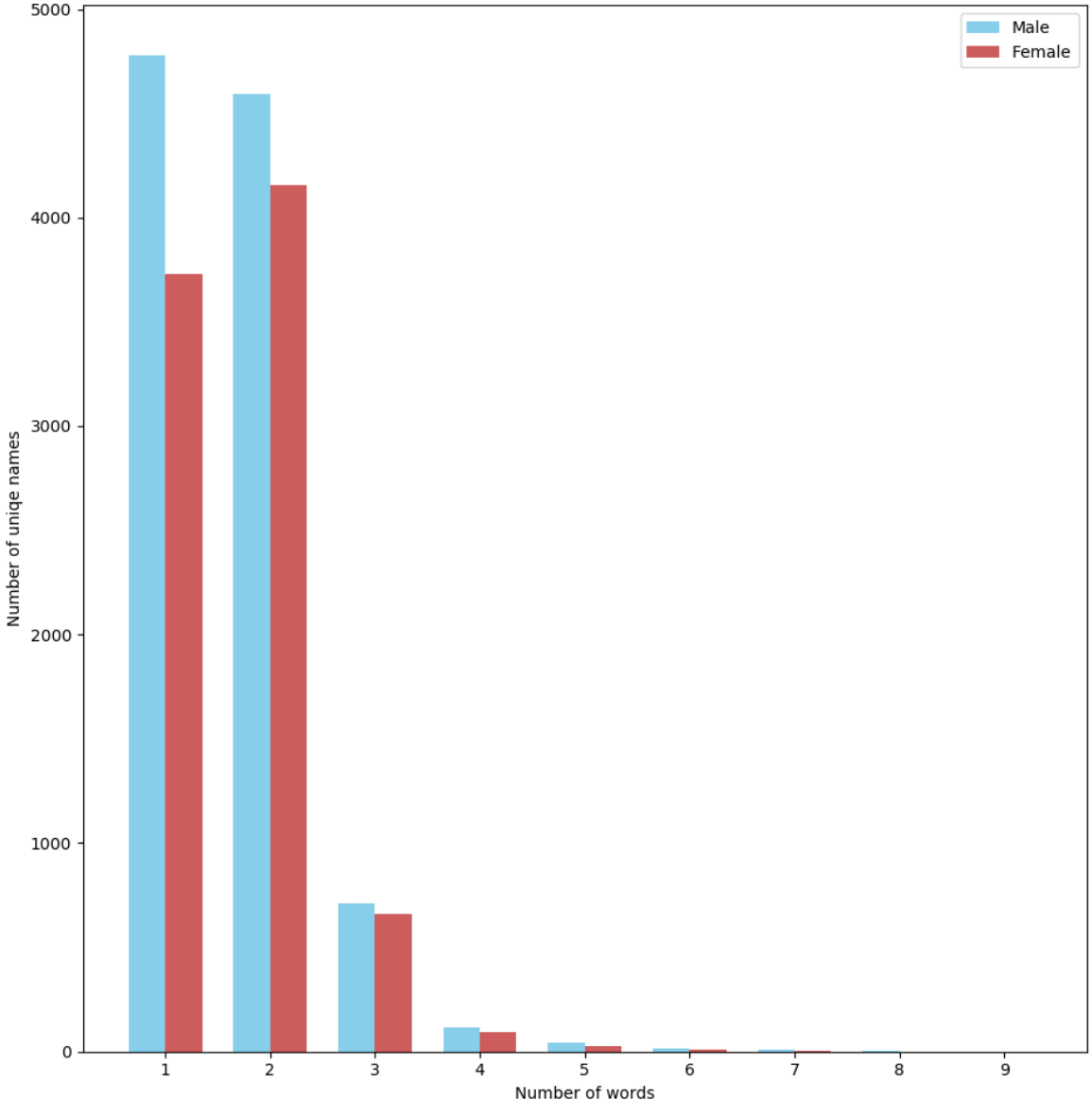

Figure: Distribution of names

Metrics

To compare our results with baseline proposed by Webster et al.[1], we use micro average of F1-scores. To compare our results with other Kaggle competitors, we used cross entropy loss $\mathcal{L}$.

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j\in\{A,B,N\}}(y_i^j * log(\sigma(\hat{y_i^j}))).$$

Where y_i^j is 1 if j is correct candidate for i^{th} example. N denotes neither case. $\hat{y_i^j}$ denotes predicted probability for class j for i^{th} example.

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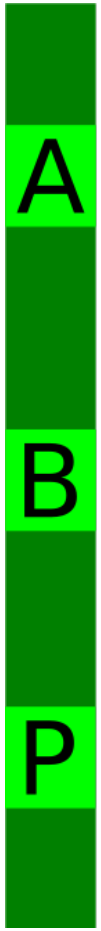
  - No need for mention scoring.
  - Different scoring functions were tried. Best we found was three layer fully connected network.

Architecture



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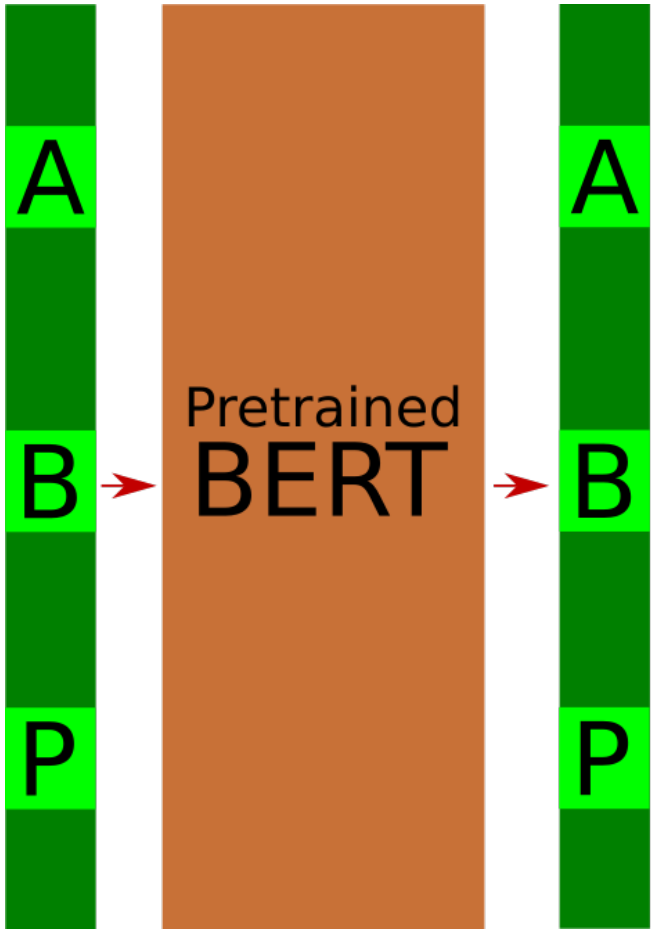

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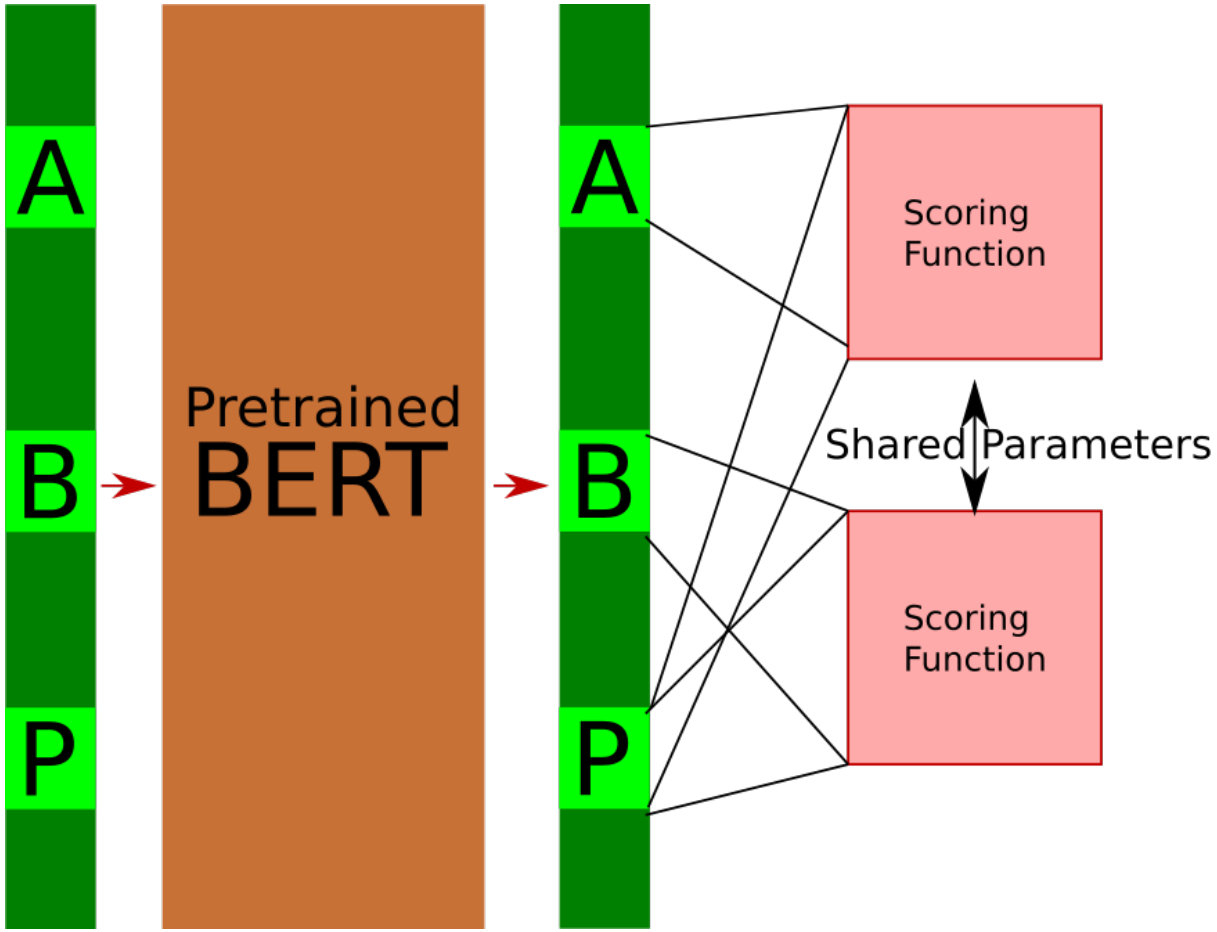

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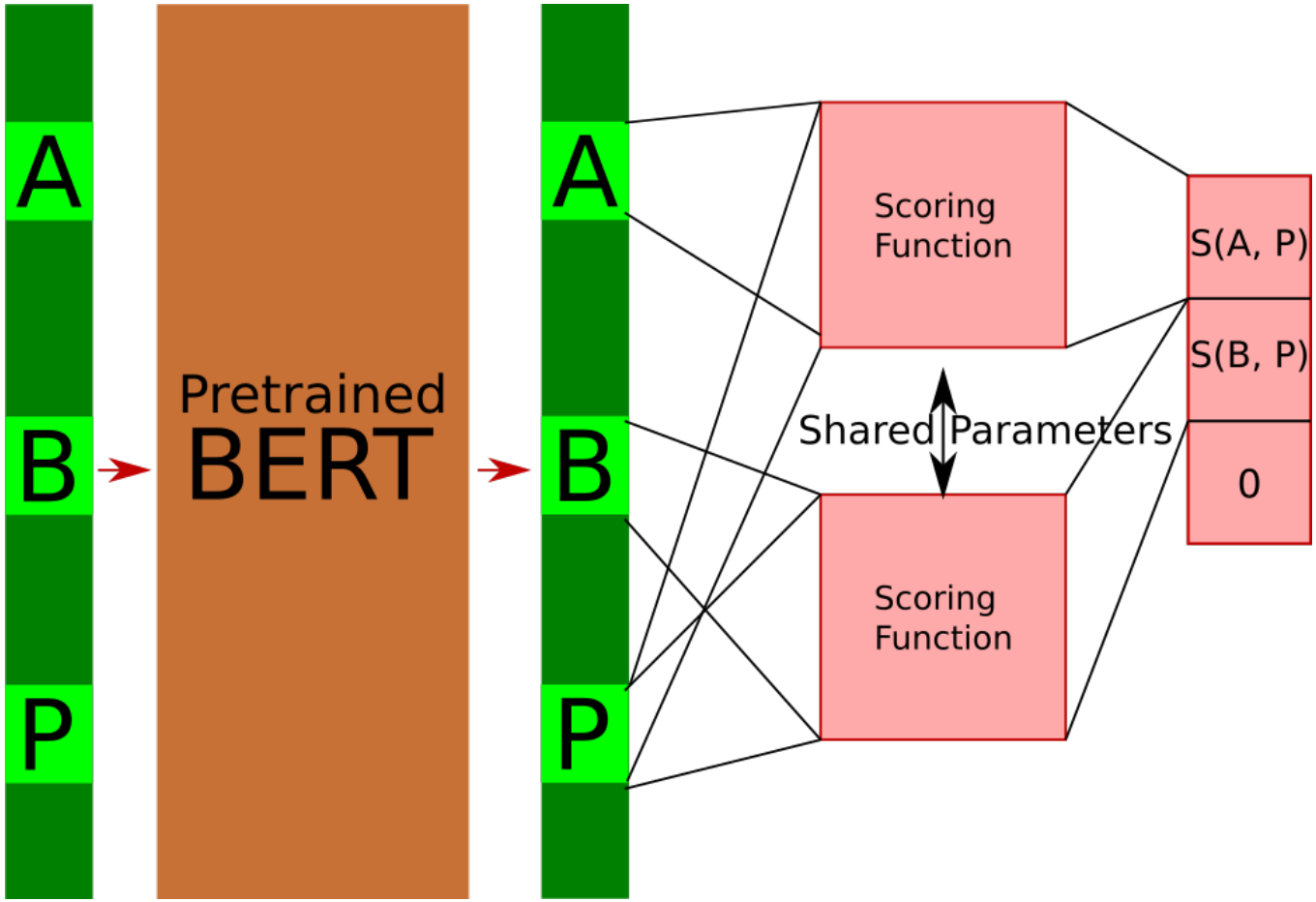

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- Best results were obtained without RNN, with weight decay of 0.001 and dropout of 0.5. Adam optimization was used.

Baselines

From Webster et al. [1]

	M	F	O
Wiseman et al. [4]	68.4	59.9	64.2
Lee et al. [3]	67.2	62.2	64.7

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Ours

An SVM trained on the output of 8th layer BERT base. (input to SVM was 768*3 dimensional vector)

	M	F	O
SVM-8	**77.10**	**79.10**	**78.10**

Stage 1

	M	F	O
SVM-8	77.10	79.10	78.10
MLP	89.10	88.00	88.55
MLP-attn	89.50	88.40	88.95
MLP-dpr	88.90	88.70	88.80
MLP-dpr-attn	90.10	87.90	89.00

Table: F1 score Results

	M	F	O
SVM-8	0.5127	0.5077	0.5102
MLP	0.2669	0.3412	0.3041
MLP-attn	0.2828	0.3252	0.3040
MLP-dpr	0.2752	0.3187	0.2969
MLP-dpr-attn	0.2706	0.3367	0.3036

Table: Cross Entropy Loss on stage 1 test set

Stage 2

	O
SVM-8	0.7809
RNN-MLP	0.3529
MLP	0.2462
MLP-attn	0.2545
MLP-dpr	0.2727
MLP-dpr-attn	0.2517
Kaggle First	0.1366
Kaggle 25th	0.2403

Table: Cross Entropy Loss on stage 2 test set

	precision	recall	f1-score	support
A	0.8635	0.9533	0.9062	856
B	0.9219	0.8930	0.9072	925
Neither	0.8113	0.5890	0.6825	219

Table: Precision-Recall of MLP

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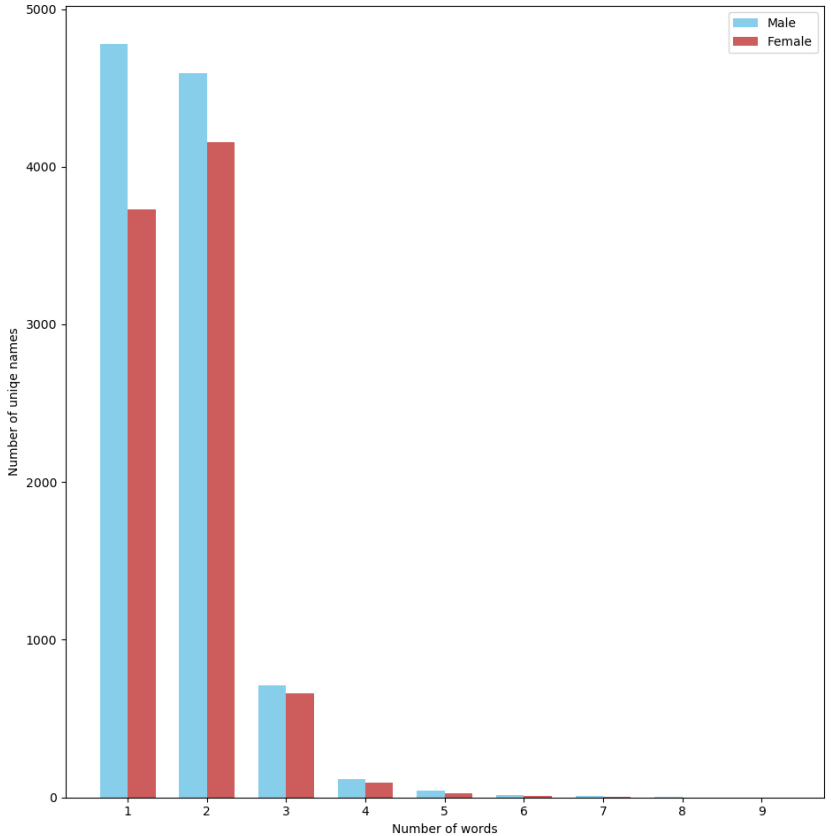

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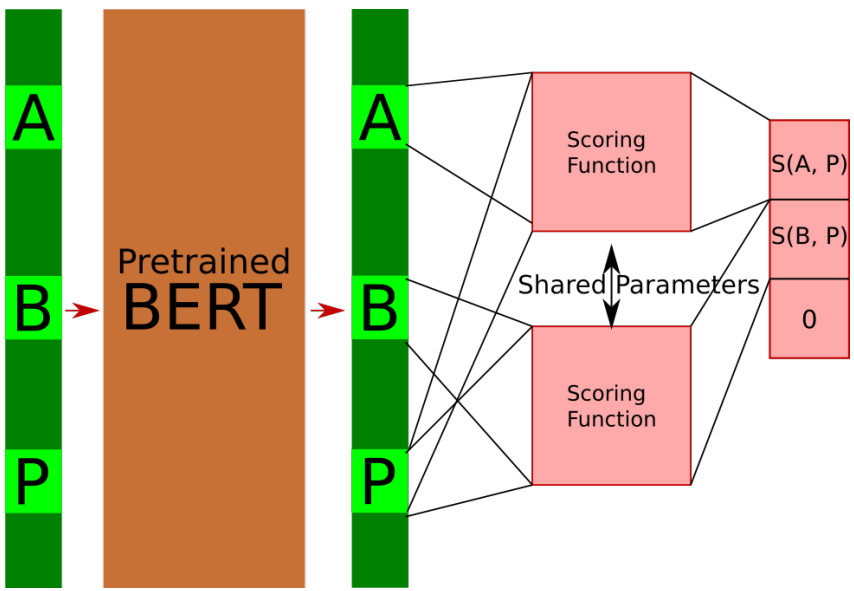

Thank You

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