What does the sea say to the shore?
A BERT based DST approach for speaker to dialogue attribution in novels

Carolina Cuesta-Lazaro, Animesh Prasad, Trevor Wood
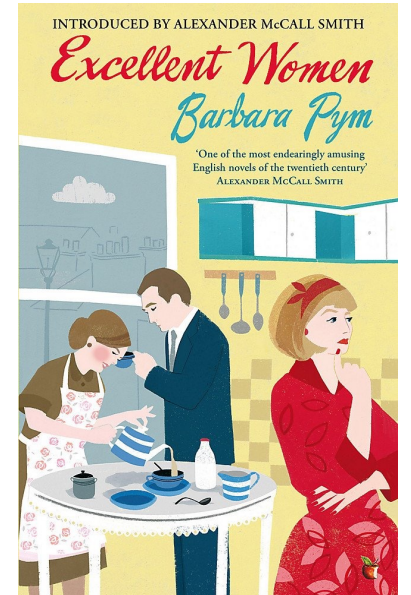
Durham University

amazon alexa

"I hope it is the best quality incense? I believe it varies."

"Yes, I've seen advertisements," I admitted, **"and they have different names. Lambeth is very expensive, but Pax is quite cheap. It seems as if it ought to be the other way round."**

"And have you dozens of glamorous acolytes?"

"Well ..." I hesitated, remembering Teddy Lemon, our Master of Ceremonies, with his rough curly hair and anxious face, and his troop of well-drilled, tough-looking little boys, "they are very nice good boys, but perhaps you should go to a Kensington church if you want to see glamorous acolytes."

"I hope it is the best quality incense? I believe it varies." ROCKINGHAM NAPIER

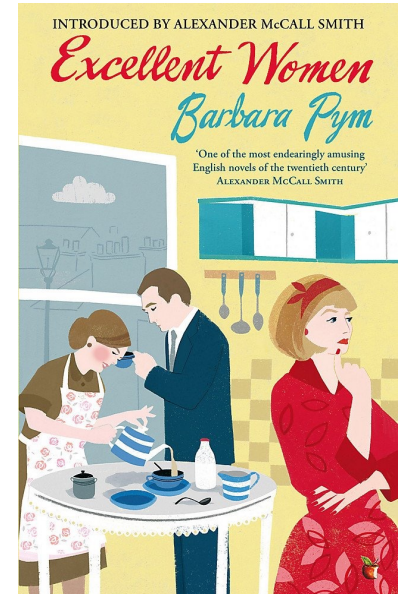"Yes, I've seen advertisements," I admitted, "and they have different names. Lambeth is very expensive, but Pax is quite cheap. It seems as if it ought to be the other way round." MILDRED LATHBURY

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INTRODUCED BY ALEXANDER McCALL SMITH

Excellent Women
Barbara Pym

'One of the most endearingly amusing English novels of the twentieth century'
ALEXANDER McCALL SMITH

MILDRED LATHBURY

ROCKINGHAM NAPIER
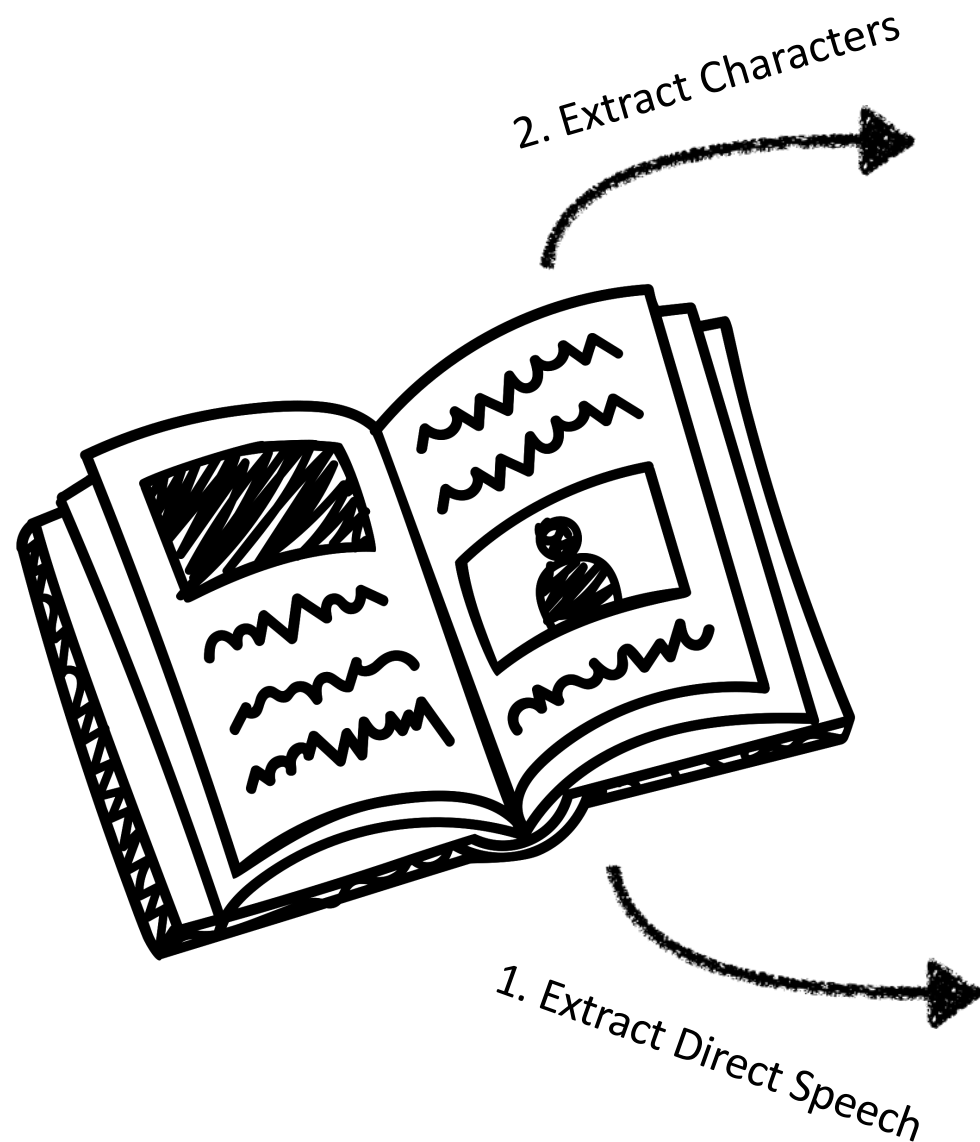
Also known as Miss Lathbury
Female
Early 30s
Strong and Independent

Also known as Rocky and Elena's husband
Male
Early 30s
Attractive, adventurous, and full of confidence

2. Extract Characters

WALDO   OUTLAW   WILMA

1. Extract Direct Speech
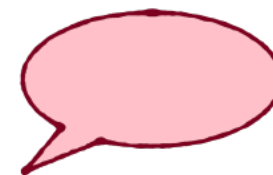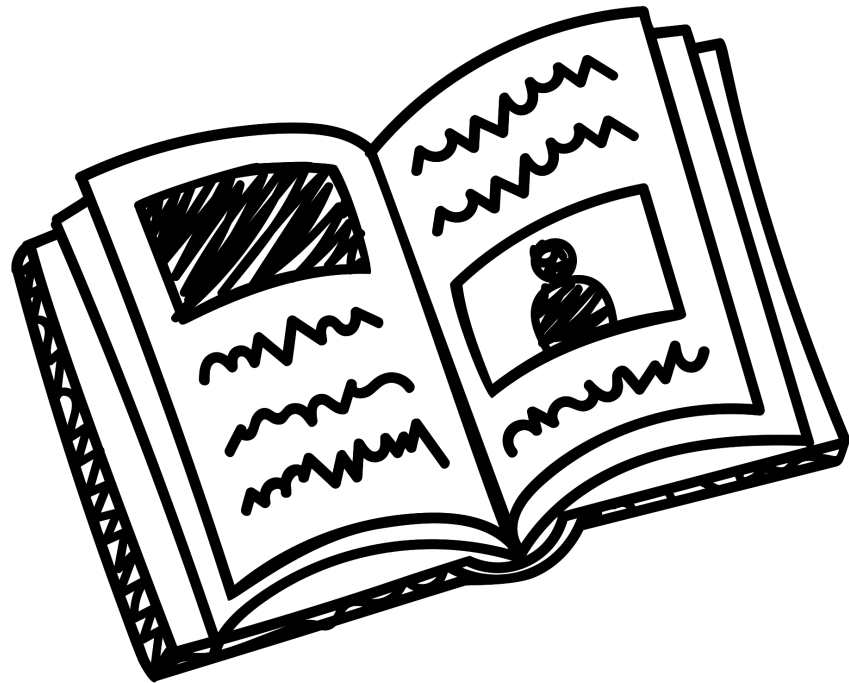
WALDO

OUTLAW

WILMA

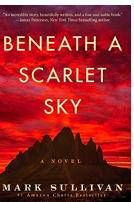3. Matching

Identifying characters the easy way

Leyers returned the salute with less enthusiasm . Rauff was about to leave , when he fixed on Pino for several seconds . Pino could feel his attention dancing all over him .

Subject

"Vorarbeiter , " General Leyers **called** . "We are leaving . Bring the car around . "

Subject

"Jawohl , General , " Pino **said** in his best German , and then hurried past the two Nazi officers , never once looking at Rauff , but feeling his flat dark eyes fixed on him .

Using Named Entity Recognition

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NORP **PERSON** **ORG**

BENEATH A SCARLET SKY

A NOVEL

MARK SULLIVAN
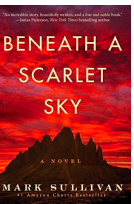
How these solutions stack?

NER: Inferred with Muzny et al., EACL 2017.

Rule Based: Explicit dialogue attribution signals

Model	F1-Score	Precision	Recall
NER	0.74 ± 0.1	0.82 ± 0.08	0.69 ± 0.14
Rule-based	0.78 ± 0.1	0.85 ± 0.07	0.76 ± 0.11

Are they the same person?

Type	Freq	Example ([mentions] → entity)
Full Name Variation	67%	[Harry, Potter, Mr. Potter, Harry Potter] → HARRY POTTER)
Dimunitives	7%	[Lizzy, Eliza] → ELIZABETH
Professional	15.5%	[the cook] → JOHN KING SILVER
Relational	5.5%	[her father] → MR. BENNET
Others	5%	[the cimmerian] → CONAN

Clustering Characters

Pino Lella

Pino

Michelle

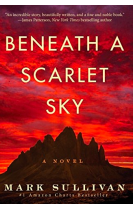Pino's father

Il Duce

Mussolini

Benito Mussolini

Father
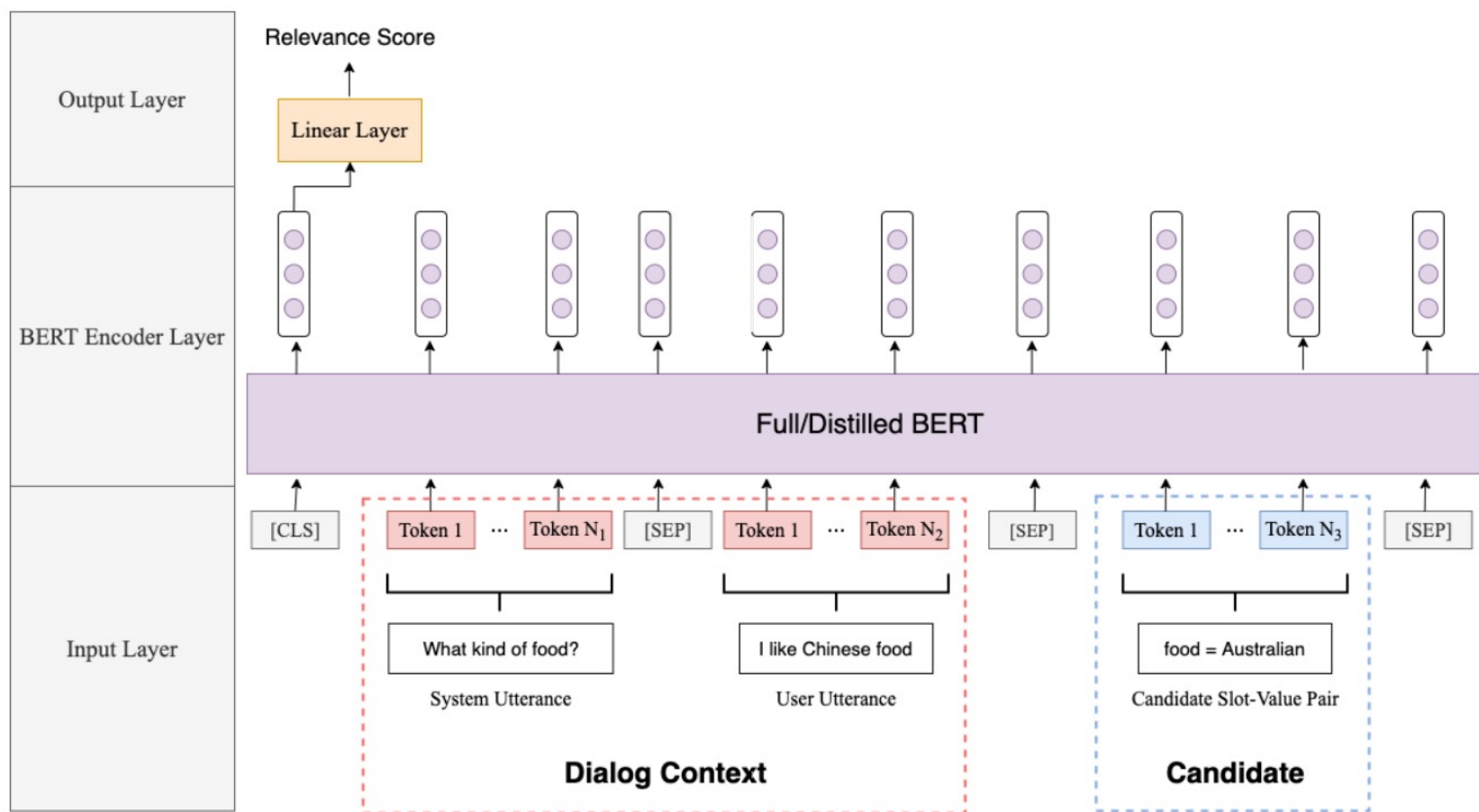
Father Re

The dictator

The priest

How these solutions stack?

Coreference: Inferred with Muzny et al., EACL 2017.

Rule Based: Salutation and Surname Compatibility

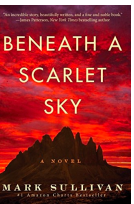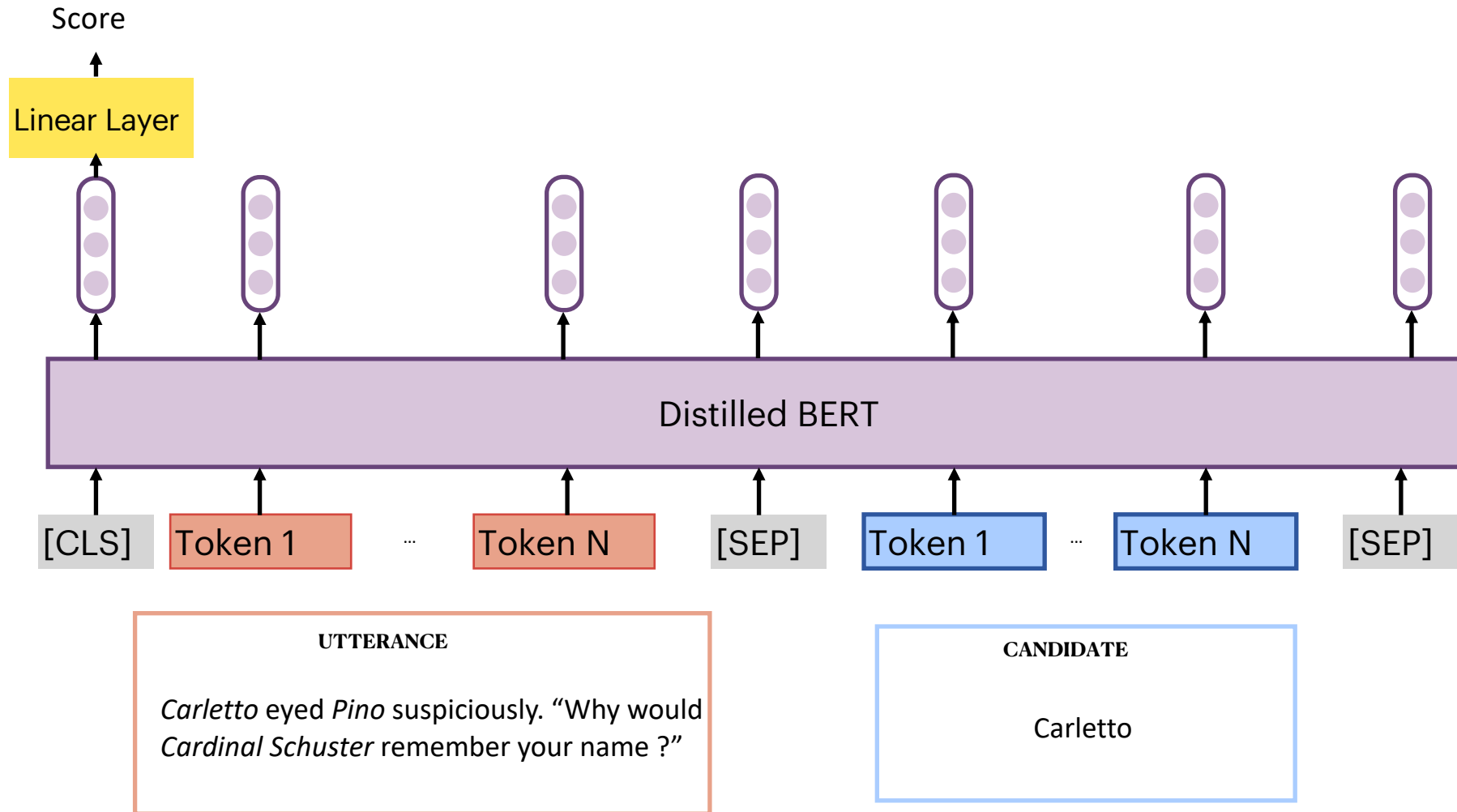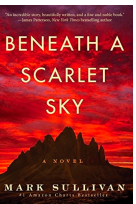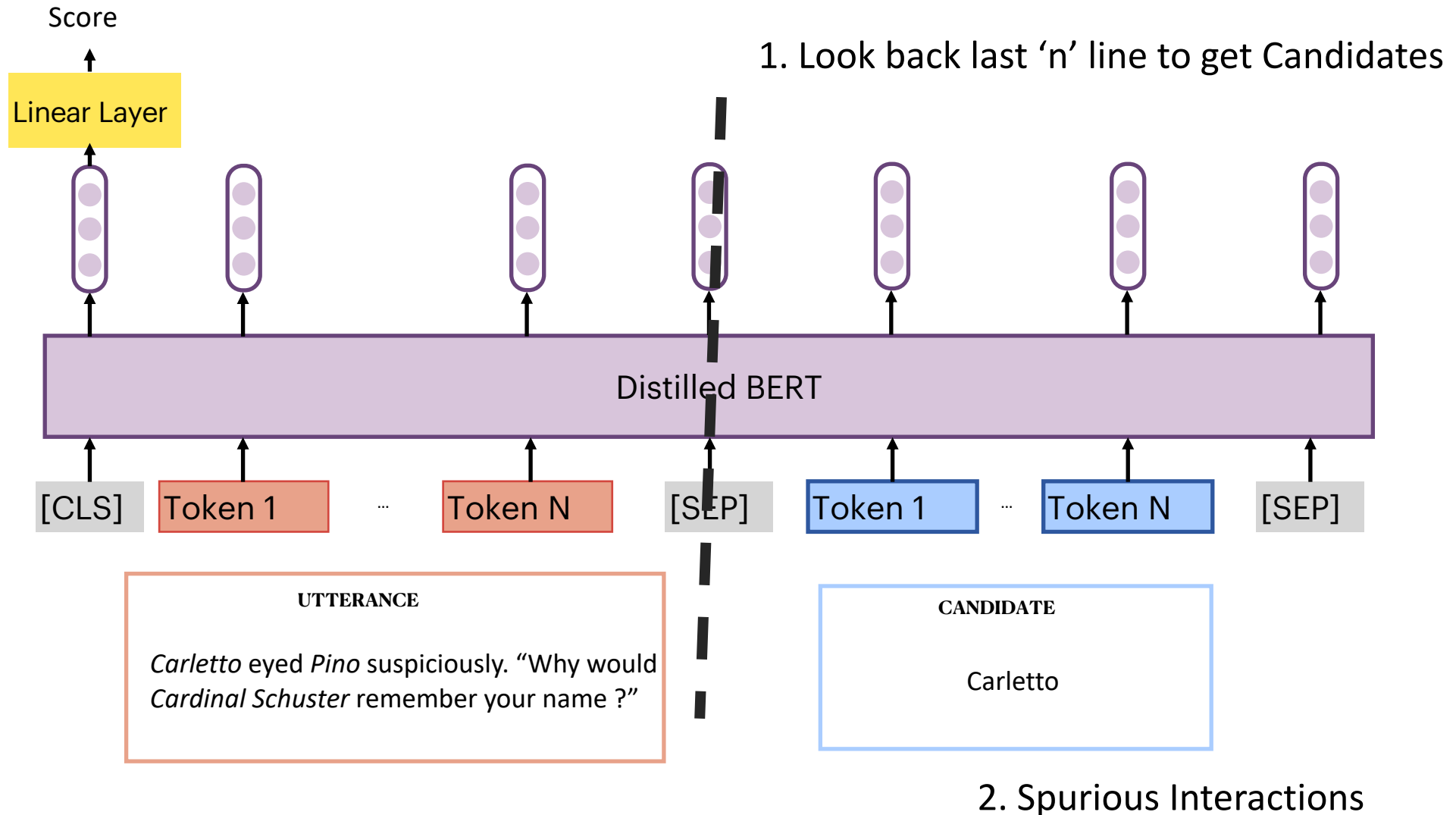| Model	F1-Score	Precision	Recall
Coreference	0.73 ± 0.1	0.97 ± 0.08	0.60 ± 0.14
Rule-based	0.86 ± 0.08	0.94 ± 0.07	0.79 ± 0.11

Attributing Speakers as Dialogue State Tracking

Courtesy Lai et al, ICASSP 2020

One step at a time: Explicit speakers

One step at a time: Explicit speakers

Score

Linear Layer

1. Look back last 'n' line to get Candidates

Distilled BERT

[CLS] Token 1 … Token N [SEP] Token 1 … Token N [SEP]

UTTERANCE

Carletto eyed *Pino* suspiciously. "Why would *Cardinal Schuster* remember your name ?"

CANDIDATE

Carletto

2. Spurious Interactions

Stable speaker representations

Uses average for multi-token names

Distilled BERT

[CLS]   Carletto Token   ...   Pino Token   ...   Schuster Token   ...   Candidate N Token   [SEP]

UTTERANCE

Carletto eyed *Pino* suspiciously. "Why would *Cardinal Schuster* remember your name ?"
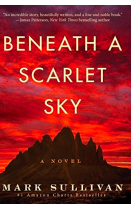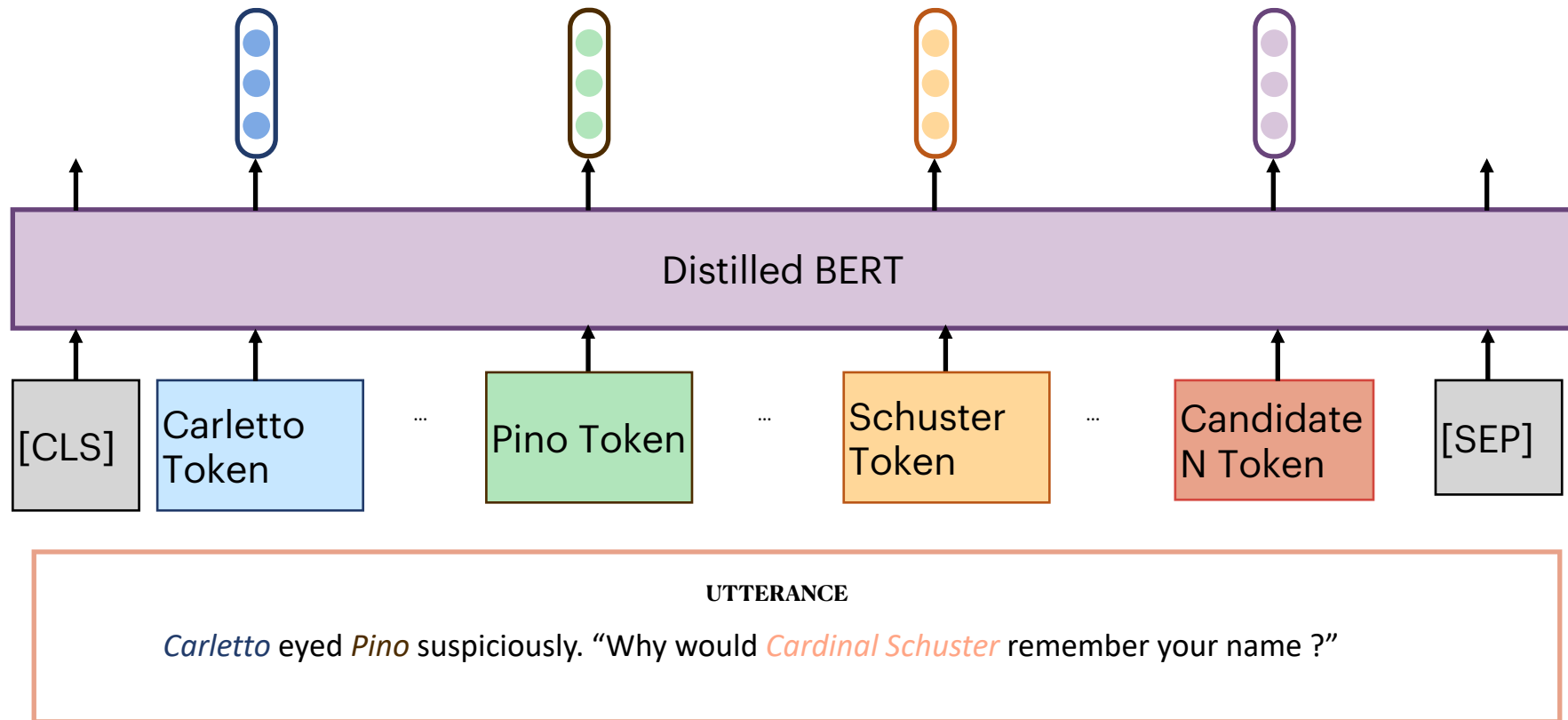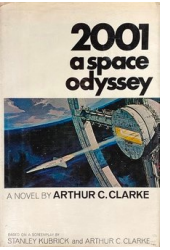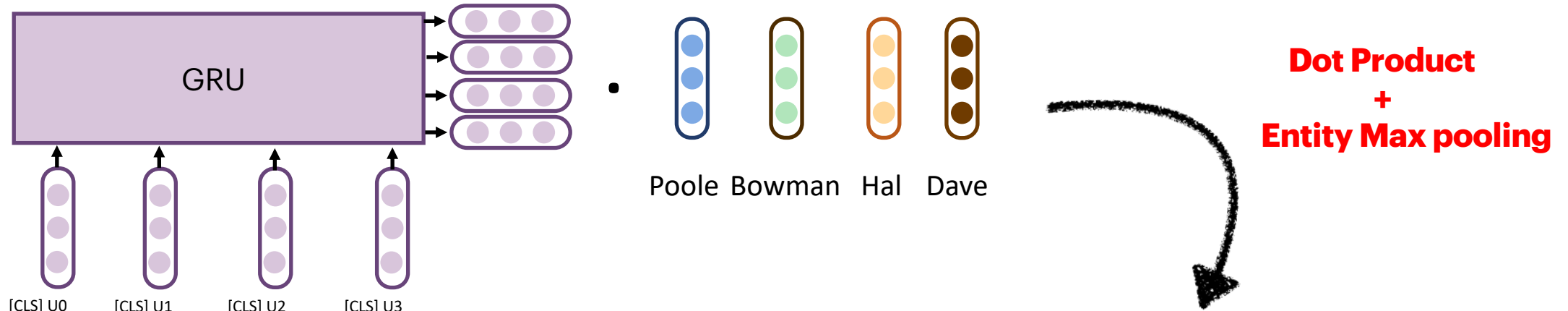
Summarising conversations

CONVERSATION

U0: *Poole* was asleep, and *Bowman* was reading on the control deck, when *Hal* announced:

U1: "Er- *Dave*, I have a report for you"

U2: "What's up?"

U3: "We have another bad AE-35 unit. My fault predictor indicates failure within twenty-four hours."

Dot Product
+
Entity Max pooling

U1

P(POOLE|u)

P(BOWMAN|u)

P(HAL|u)

U2

P(POOLE|u)

P(BOWMAN|u)

P(HAL|u)

U3

P(POOLE|u)

P(BOWMAN|u)

P(HAL|u)

Learning to take turns with Conditional Random Fields

$$\text{Score}(\mathbf{y}|\mathbf{u}) = \sum_{n=0}^{N} \mathbf{E}_n(y_n|\mathbf{u}) + \sum_{n=0}^{N-1} V_{y_n, y_{n+1}}$$

Entity logits from RNN

Transition Matrix

$$V = \begin{pmatrix} (-)X & Y & Y \\ Y & (-)X & Y \\ Y & Y & (-)X \end{pmatrix} \begin{array}{l} \text{Character 0} \\ \text{Character 1} \\ \text{Character 2} \end{array}$$

Character 0   Character 1   Character 2

How does this solutions stack?

Our (Proposed) model

Nearest mention Baseline

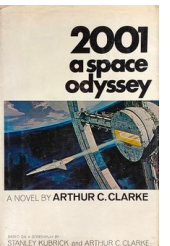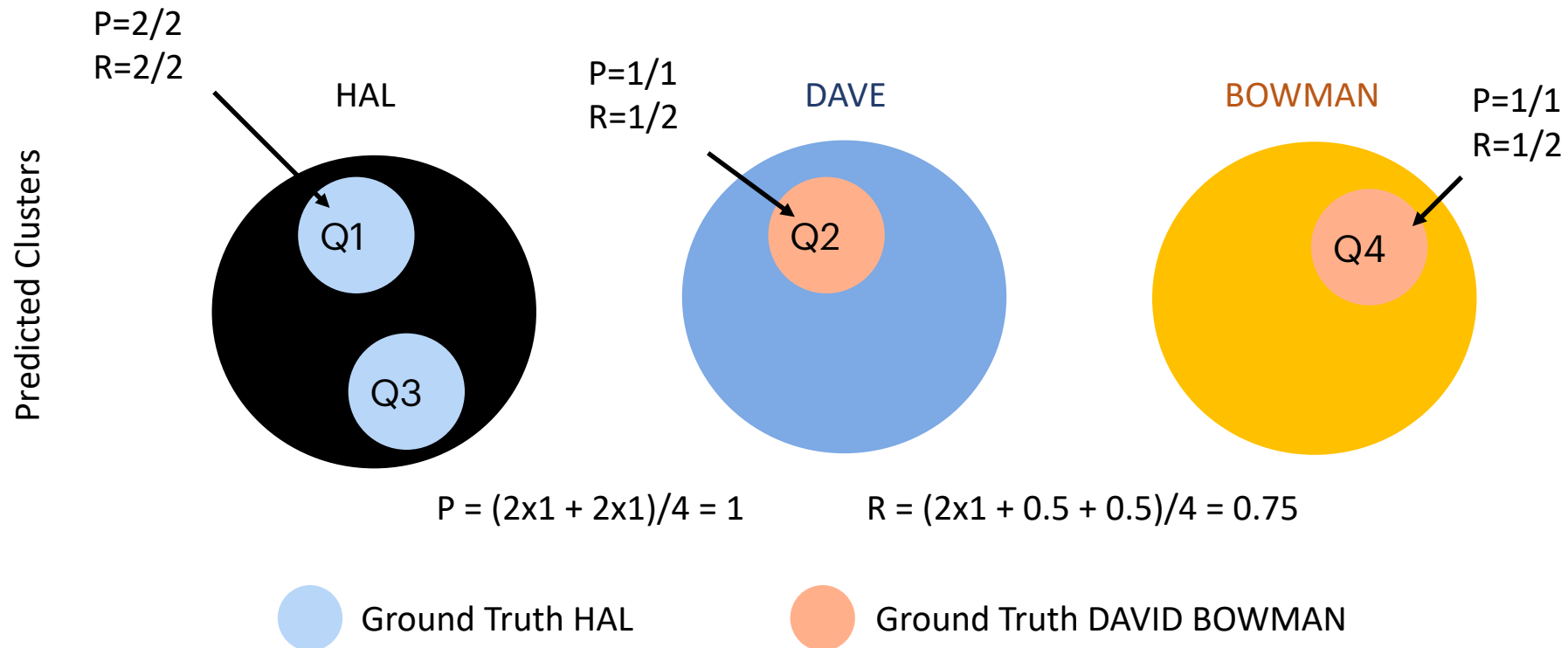| Model	F1-Score	Precision	Recall
Our model	0.78 ± 0.06	0.81 ± 0.06	0.77 ± 0.06
NM	0.54 ± 0.08	0.57 ± 0.06	0.54 ± 0.08

How can we evaluate the pipeline? Clustering!

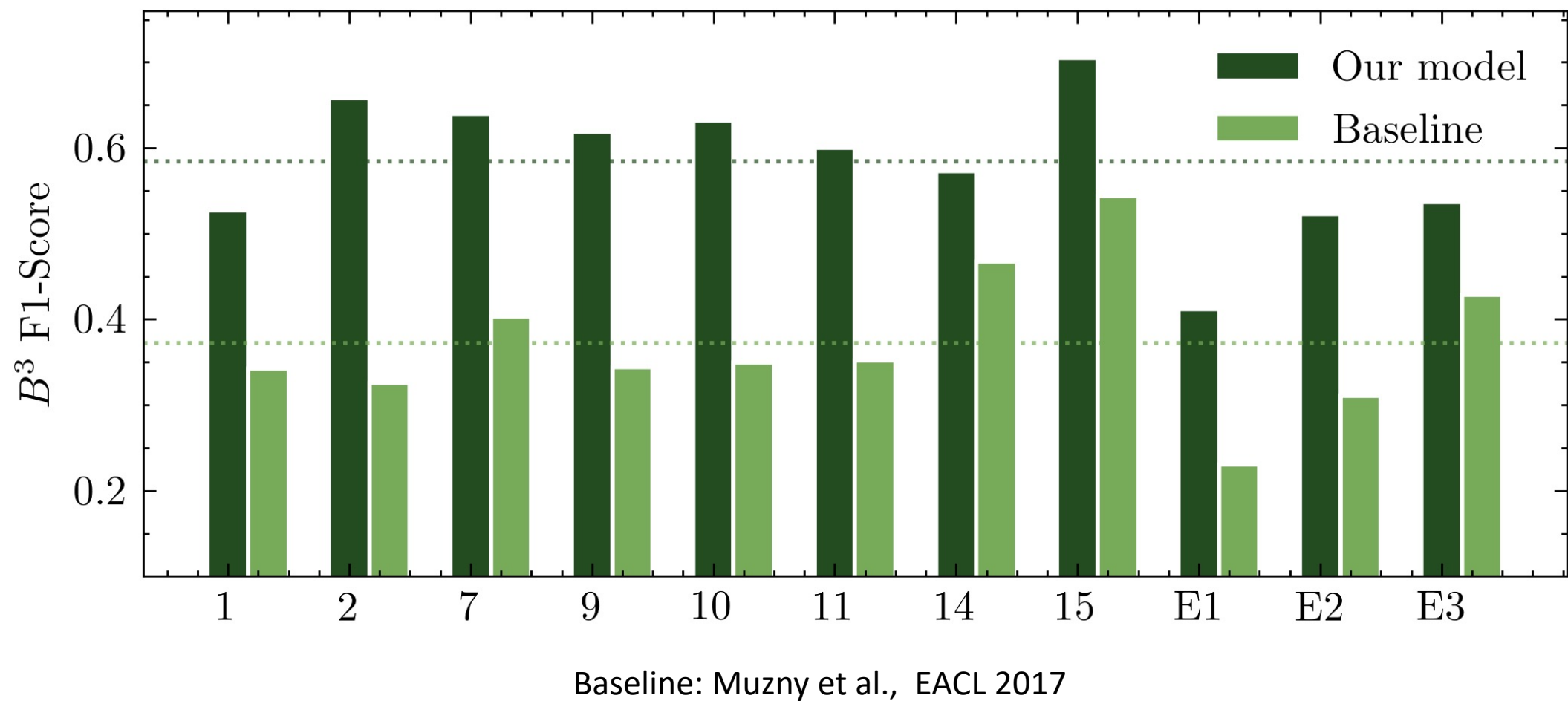**U1:** "Er- *Dave*, I have a report for you"

U2: "What's up?"

U3: "We have another bad AE-35 unit. My fault predictor indicates failure within twenty-four hours."

U4: "I don't understand it, Hal", said Bowman

P=2/2
R=2/2

P=1/1
R=1/2

P=1/1
R=1/2

HAL

DAVE

BOWMAN

Predicted Clusters

Q1

Q3

Q2

Q4

P = (2x1 + 2x1)/4 = 1   R = (2x1 + 0.5 + 0.5)/4 = 0.75

Ground Truth HAL   Ground Truth DAVID BOWMAN

Leave one out evaluation
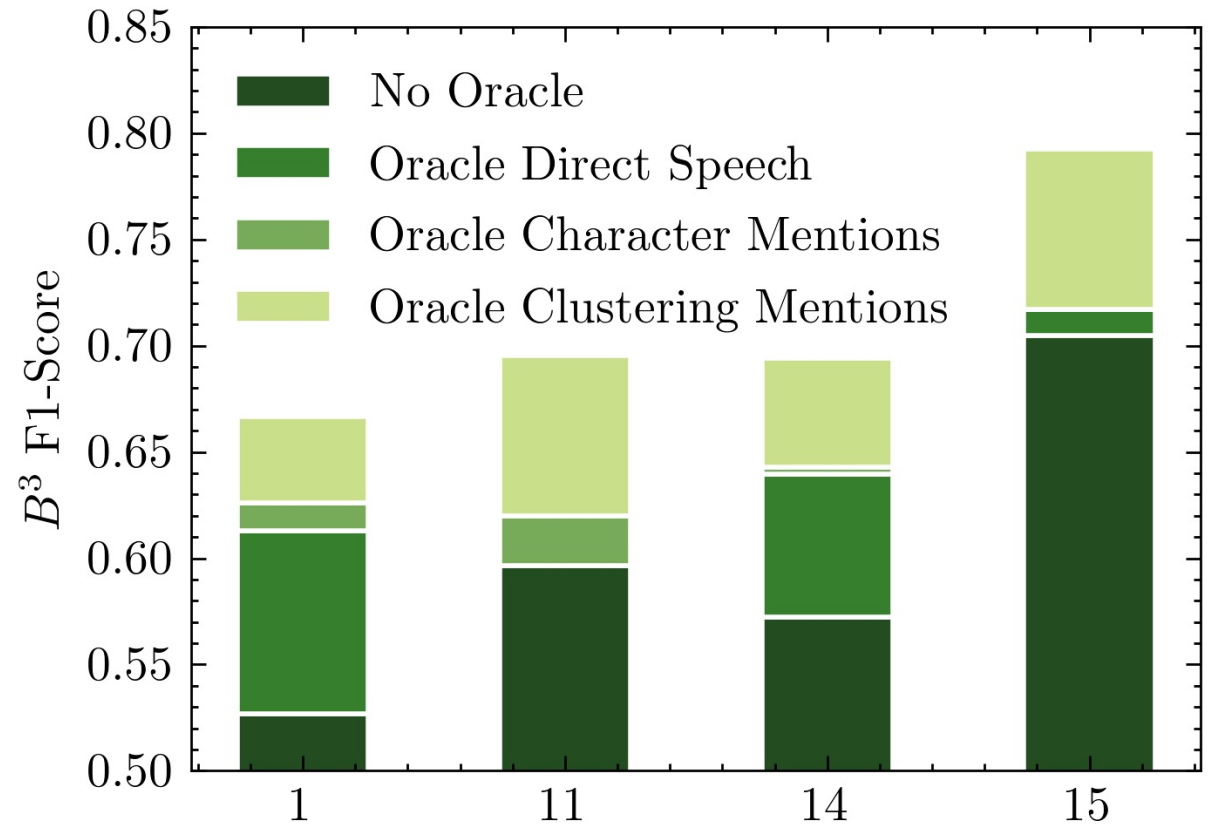

Baseline: Muzny et al., EACL 2017

Challenges? (And easy wins!)

Unification of pipeline approaches, maybe as additional targets

- NER
- Co-reference

An instance of local versus global processing

The good and the bad

He was met by Tuthmes , tall , slender , dusky , with the straight features of his caste .

"What are you saying , Afari ? " **THUTHMES**

Afari closed the door before he answered; he was panting as if from a long run . He was shorter than Tuthmes , and the negroid was more predominant in his features .

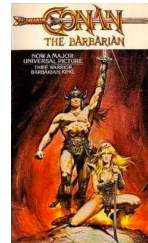"Amboola ! He is dead ! In the Red Tower !

" **THUTHMES**

"What ? " exclaimed Tuthmes . "Tananda dared execute him ? " **THUTHMES**

"No ! No , no ! [...] Tuthmes , it is the work of some demon ! " **MAN**
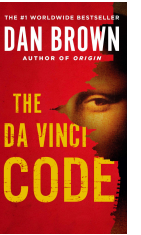
"When was this done ? " **THUTHMES**
"Sometime about midnight . [...]. " **THUTHMES**
Error: Afari is not in the character list!

Tall and lissome , Dr Brooks moved with the assertive gait of an athlete . [...]

"Dr Marconi doesn't speak much English , " she said , sitting down beside him , "and he asked me to fill out your admittance form . " She gave him another smile . **DR SIENNA BROOKS**

"Thanks , " Langdon croaked . **ROBERT LANGDON**

"Okay , " she began , her tone businesslike . "What is your name ? " **DR SIENNA BROOKS**

It took him a moment . "Robert … Langdon . " **ROBERT LANGDON**

She shone a penlight in Langdon's eyes . "Occupation ? " **DR SIENNA BROOKS**

This information surfaced even more slowly . "Professor . Art history … and symbology . Harvard University . " **ROBERT LANGDON**

Thank You and Questions!