

A CASE STUDY:
DETECTING COUNSELOR REFLECTIONS
IN MOTIVATIONAL INTERVIEWING

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STORY

MISC: **hard** to learn, **costly** to implement, **does not scale**, inconsistent, boring?

STORY

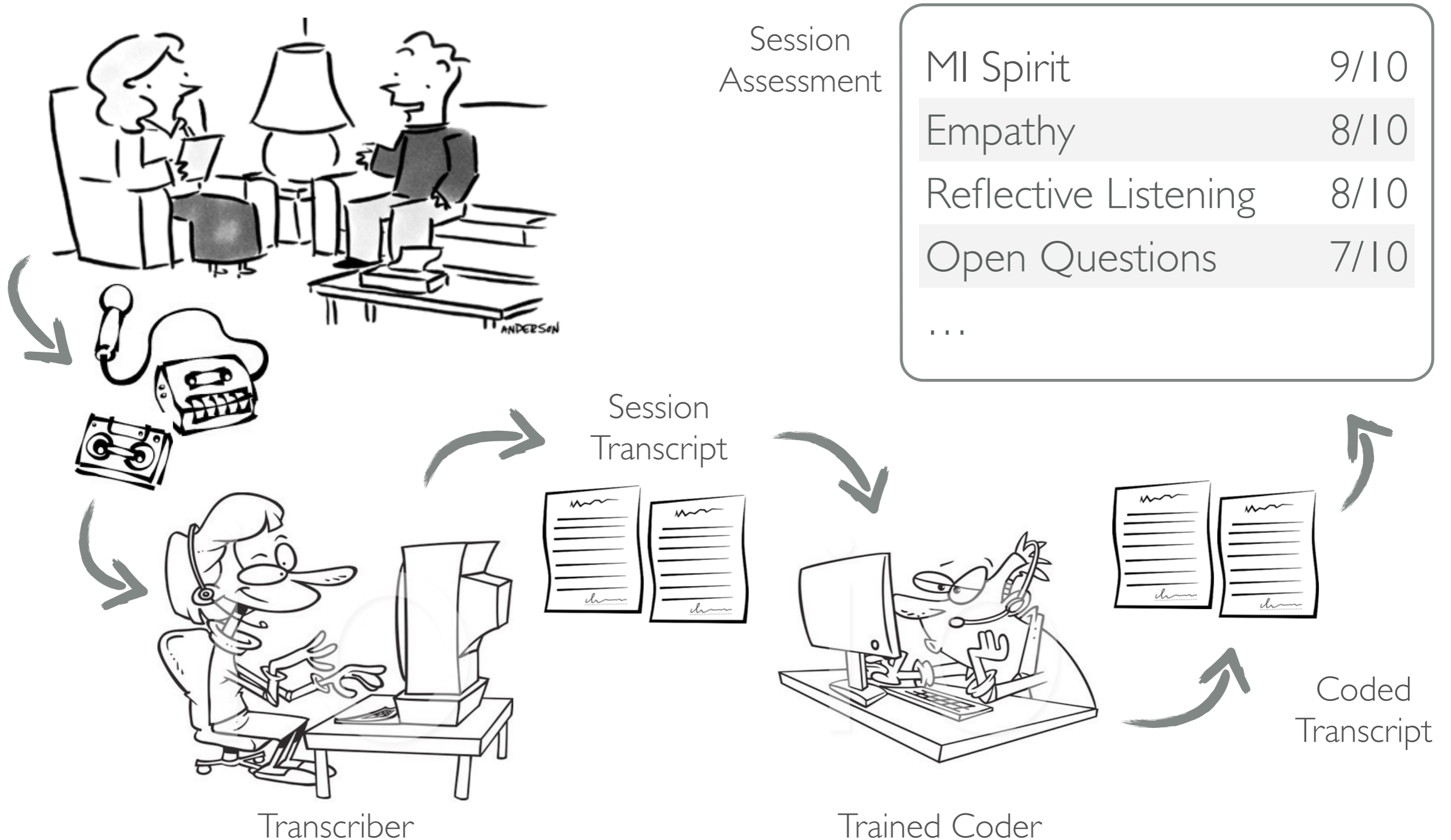
MISC: **hard** to learn, **costly** to implement, **does not scale**, inconsistent, boring?

Automatic Coding or: How I Learned to Stop Worrying and Love MISC

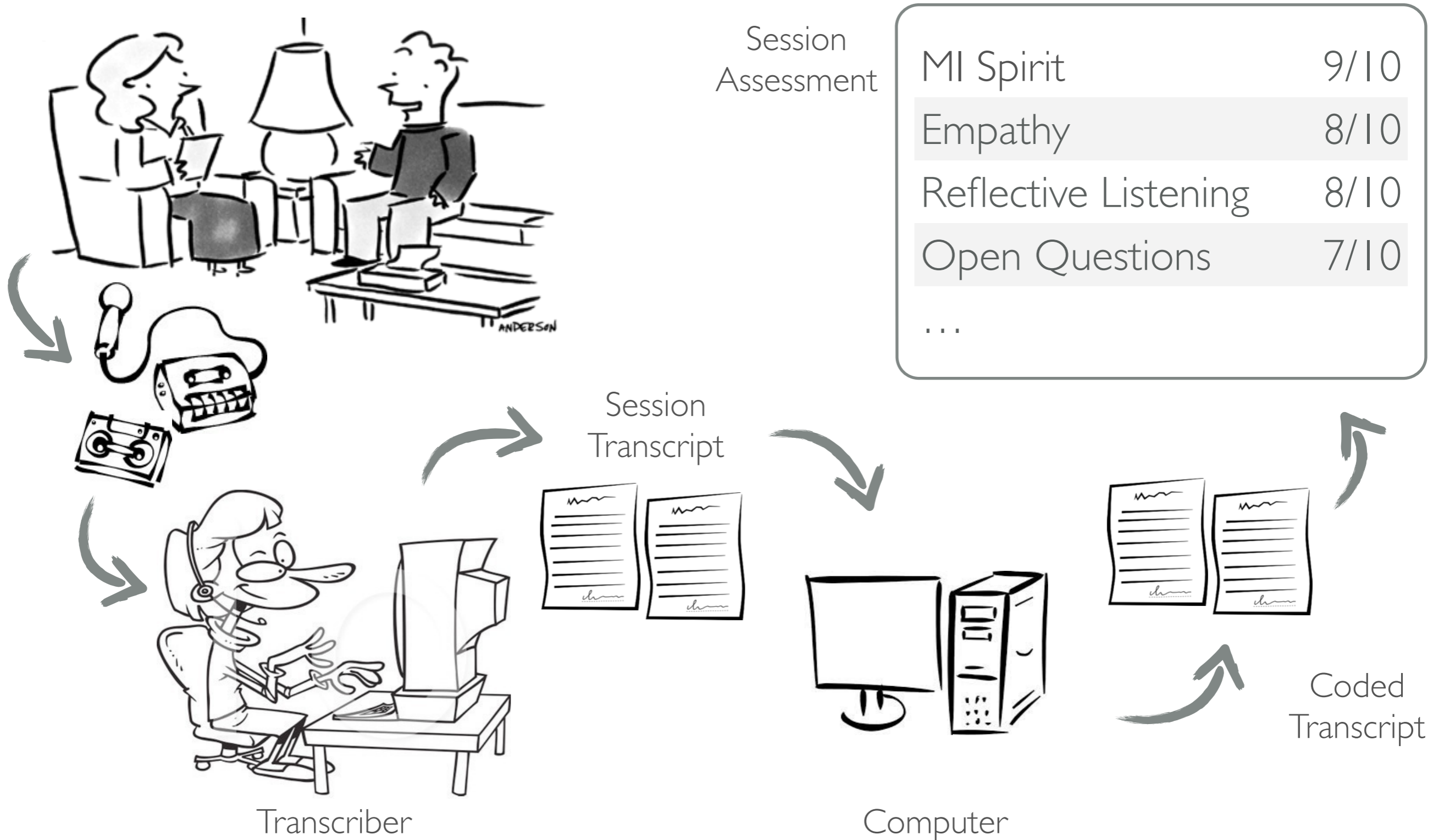
“Gee, I wish I had one of them automatic MI assessment machines.”

General “Buck” Turgidson

MI RESEARCH PROCESS



AUTOMATIC CODING



AUTOMATIC CODING

T On the one hand, you have decided that to quit drinking is going to be the best thing for you...



Therapist (T)
you
you have decided
for you
best thing for you



Code
Predictor



RES	0.4
REC	0.3
QU	0.1
FA	0.1
...	...

independent variables
(a.k.a. features)

think of multinomial
logistic regression

predictions



Session
Transcripts



AUTOMATIC CODING

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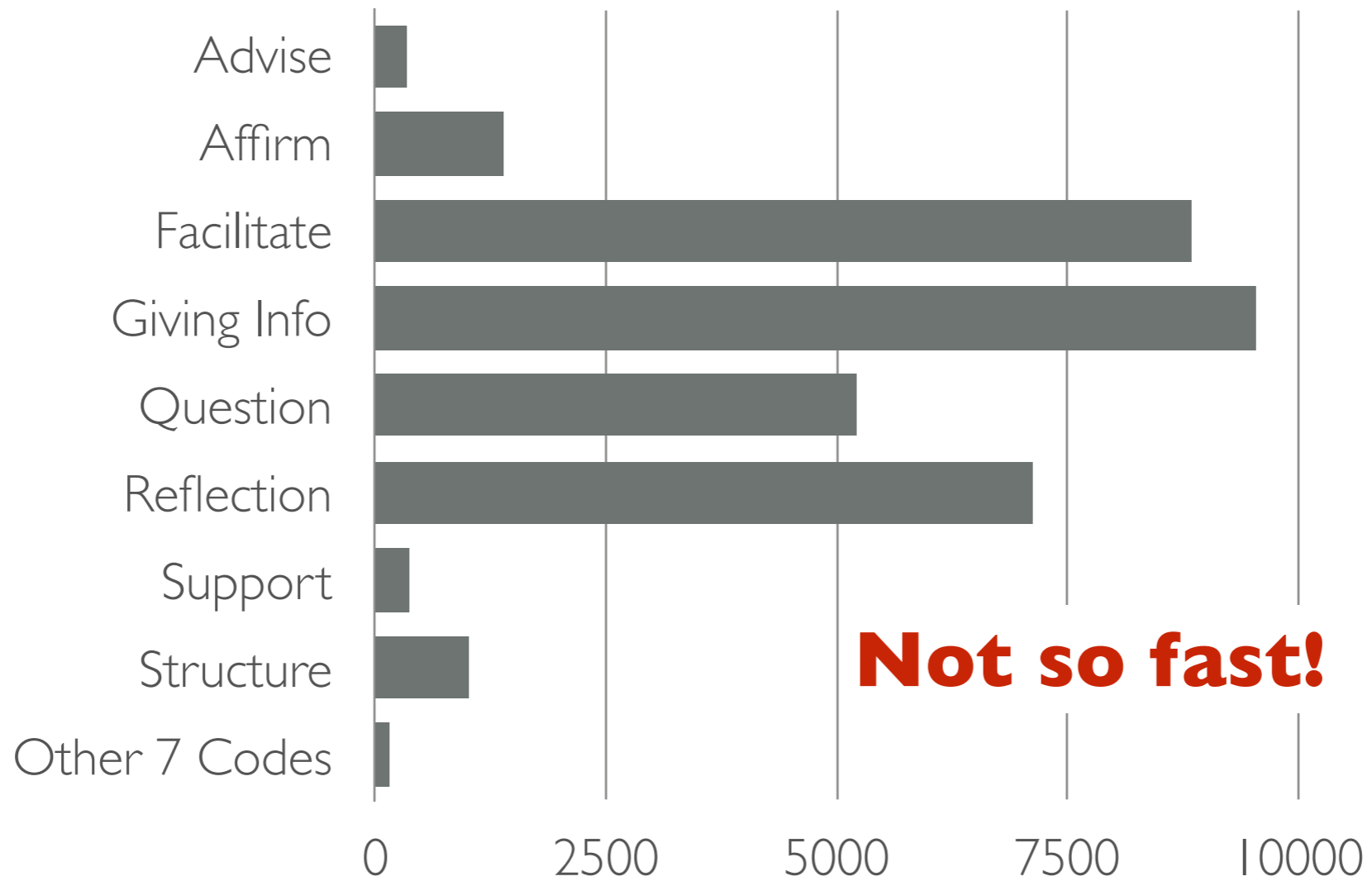
Session
Transcripts



Coded
Transcripts

AUTOMATIC CODING

Distribution of Counselor Codes



57 sessions, 2 coders per session (on average)

RES

Not so fast!

Session
Transcripts



Coded
Transcripts

AUTOMATIC CODING

T	Good morning, Susan	FA
T	I'd like to start by talking about our last conversation.	ST
...
T	What will you put in place of drinking?	QU
P	That's what I'm trying to find out.	O+
...
T	On the one hand, you have decided that to quit drinking is going to be the best thing for you...	RES
P	Uh-huh.	FN
T	and on the other hand you feel like it's going to be really tough.	REC
P	Yeah.	FN

Session
Transcripts



Coded
Transcripts

REFLECTION DETECTION

T	Good morning, Susan	TH
T	I'd like to start by talking about our last conversation.	TH
...
T	What will you put in place of drinking?	TH
P	That's what I'm trying to find out.	CL
...
T	On the one hand, you have decided that to quit drinking is going to be the best thing for you...	RE
P	Uh-huh.	CL
T	and on the other hand you feel like it's going to be really tough.	RE
P	Yeah.	CL



WHY REFLECTIONS?

1. They are believed to be **critical** for MI efficacy.
2. They encode a **non-trivial** counselor behavior.
3. They are **challenging** to model/describe.

CAN LANGUAGE PREDICT REFLECTIONS?

1. Reflections are **semantically similar** to prior client talk.
2. A **common language** is shared across reflections.

Counselors tend to use predictable language constructs while reflecting, e.g. “From what I’m hearing”, “It seems like”

3. **Local dialog context** can predict reflections.

Reflections tend to occur in bursts. They usually prompt the client to confirm or deny, e.g. “Yeah”, “Not really”

Reflections

Typical reflective constructs:

repeat, rephrase or summarize

add meaning or emphasis

analogies, metaphors, similes, etc.

in response to client statement

trigger confirmation by client

collaborative, non-judgmental,
emphatic

Independent Variables

Expert knowledge driven features:

Reflections

Typical reflective constructs:

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Independent Variables

Expert knowledge driven features:

n-grams (n consecutive words)

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contextual n-grams

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meta (speaker, codes)

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- in response to client statement
- trigger confirmation by client
- collaborative, non-judgmental, emphatic

Independent Variables

Expert knowledge driven features:

n-grams (n consecutive words)

contextual n-grams

meta (speaker, codes)

similarity (n-gram sharing)

P I wouldn't mind coming here for treatment but I don't want to go to one of those places where everyone sits around crying and complaining all day. CL

T You don't want to do that. RE

T So you're kind of wondering what it would be like here. RE

P Yeah CL

n-gram:

T:=:you

T:=:you do not want

contextual n-gram:

P:-:i would not

T:+:so you are

P:+:yeah

meta:

P:T

P:T_P

CL:

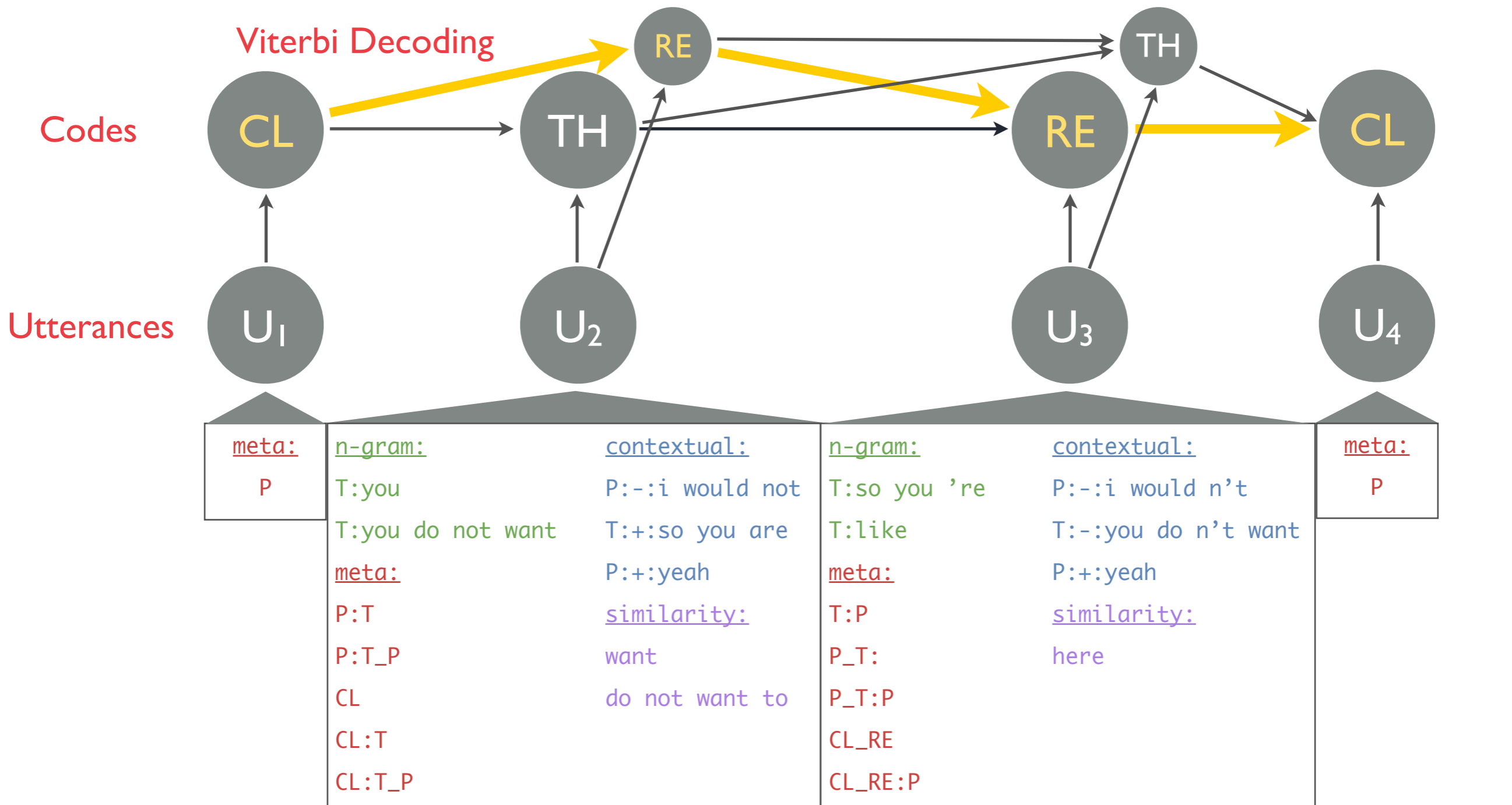
CL:T

CL:T_P

similarity:

want

do not want to



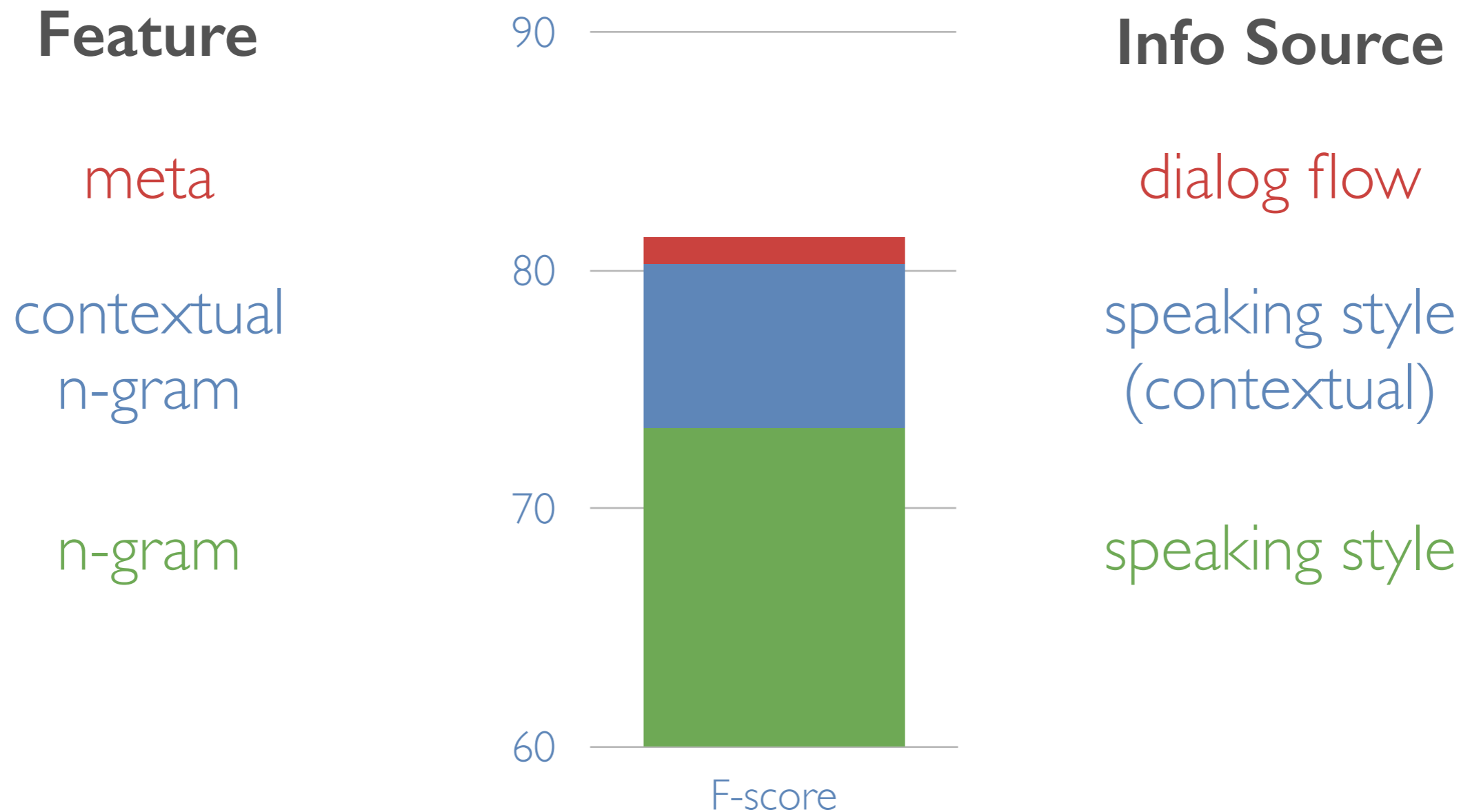
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T So you're kind of wondering what it would be like here. RE

P Yeah. CL

STYLE AND FLOW PREDICT REFLECTIONS



Average numbers from leave one out cross validation experiments.

F-score: harmonic mean of precision (positive predictive value) and recall (sensitivity)

$$\text{F-score} = 2 \times \text{TruePos} / (2 \times \text{TruePos} + \text{FalseNeg} + \text{FalsePos})$$

STYLE vs CONTENT

Reflection Production

- Is style as important as the content?
- Is reflection a local process?

Reflection Perception

- Are coders affected by the speaking style?

N-gram sharing not helpful?

- Weak feature for measuring similarity, data sparsity
- High baseline: nature of dialog + professional counselors

IN THE WORKS

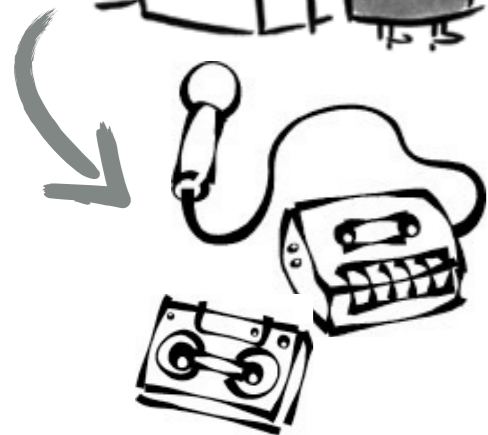
1. Extension to the larger code sets
2. Acoustic/prosodic features
3. Speech recognition instead of manual transcripts

MI RESEARCH PROCESS



Session
Assessment

MI Spirit	9/10
Empathy	8/10
Reflective Listening	8/10
Open Questions	7/10
...	



Session
Transcript



Transcriber



Trained Annotator



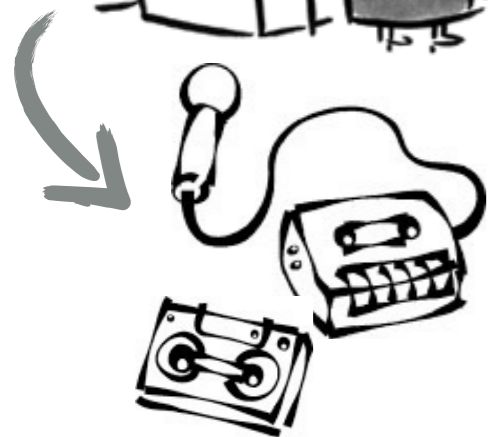
Annotated
Transcript
(MISC)

DO WE NEED ANNOTATORS?



Session
Assessment

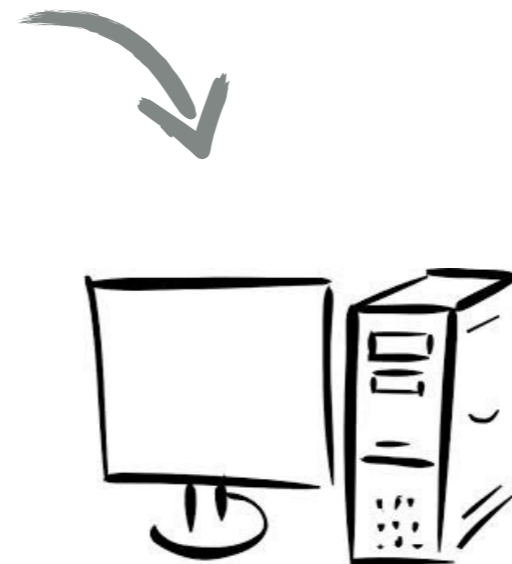
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Session
Transcript



Transcriber



Computer



Annotated
Transcript
(MISC)

DO WE NEED TRANSCRIBERS?



Session
Assessment

MI Spirit	9/10
Empathy	8/10
Reflective Listening	8/10
Open Questions	7/10
...	



Annotated
Transcript
(MISC)

DO WE NEED TRANSCRIPTS?



Session
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MI Spirit	9/10
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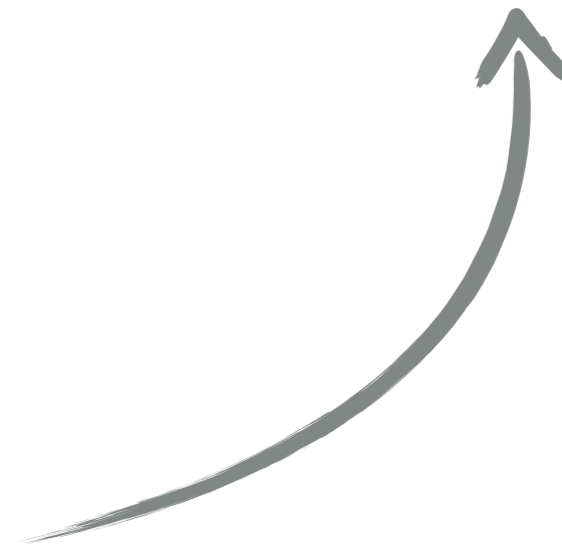
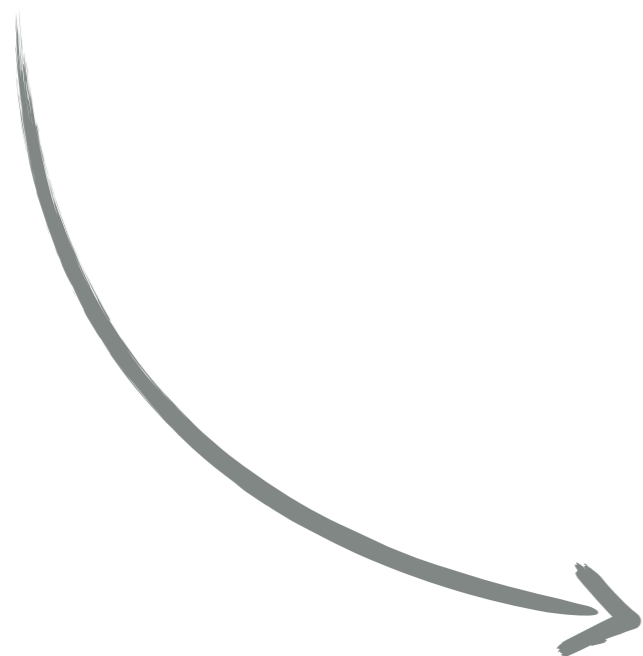


WHY NOT DO IT ONLINE?



Session
Assessment

MI Spirit	9/10
Empathy	8/10
Reflective Listening	8/10
Open Questions	7/10
...	



WHY NOT DO IT ONLINE?



Session
Assessment

MI Spirit	9/10
Empathy	8/10
Reflective Listening	8/10
Open Questions	7/10
...	

Profit!

