How Amy understands humans

x.ai makes an AI personal assistant who schedules meetings for you

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Rakesh Chada
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• Introduction to Amy
• High Level Product Architecture
• NLU challenges
• Evolution of our DS* models
• Non DL* vs DL* models
• Things we learned

DS = Data Science
DL = Deep Learning
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DS = Data Science
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Hi John. I’d be happy to meet up next week. Please work with Amy (CC’ed) to get this on the calendar. Looking forward to it. //Michael. :-)

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To: John
Cc: amy@x.ai
Subject: Re: Meeting up for coffee
Pain of Scheduling Meetings

When you receive a meeting request from your business partners or friends, what do you need to do?

Hi Rakesh,
Can we do a walk through of your O'Reilly presentation when you have time?
If you can meet with your friends, you can suggest a time range and a place to meet:

**Rakesh**

Hey Marcos,

Sure. How about tomorrow afternoon?

**Marcos**

Hi Rakesh,

Can we do a walk through of your O'Reilly presentation when you have time?
Pain of Scheduling Meetings

Then your friend can suggest a specific time on that date:

Hey Marcos,
Sure. How about tomorrow afternoon?

Hi Rakesh,
Can we do a walk through of your O'Reilly presentation when you have time?

I am swamped tomorrow. How about Wednesday morning?
Pain of Scheduling Meetings

What if that time doesn’t work for you?

Rakesh

Hey Marcos,

Sure. How about tomorrow afternoon?

Marcos

Hi Rakesh,

Can we do a walk through of your O’Reilly presentation when you have time?

Ah I have back to back meetings Wednesday morning. How about afternoon?

I am swamped tomorrow. How about Wednesday morning?
Pain of Scheduling Meetings

If that time works for your friend, he or she will accept it.

Rakesh

Hey Marcos,

Sure. How about tomorrow afternoon?

Ah I have back to back meetings Wednesday morning. How about afternoon?

Marcos

Hi Rakesh,

Can we do a walk through of your O'Reilly presentation when you have time?

I am swamped tomorrow. How about Wednesday morning?

Yes I can do Wednesday afternoon.
Pain of Scheduling Meetings

Reply to Confirm. Is that the end?

Hey Marcos,
Sure. How about tomorrow afternoon?

Ah I have back to back meetings Wednesday morning. How about afternoon?

Awesome. Looking forward to it.

Hi Rakesh,
Can we do a walk through of your O'Reilly presentation when you have time?

I am swamped tomorrow. How about Wednesday morning?

Yes I can do Wednesday afternoon.
Hi Rakesh,
Can we do a walk through of your O'Reilly presentation when you have time?
Hi Rakesh,
Can we do a walk through of your O'Reilly presentation when you have time?

Hi Rakesh,
Sure. I'll have Amy coordinate it. Amy, can you find a time for us? Thank you.

Cc: amy@x.ai
Solution with Amy

The back and forth is handled by Amy.

Hey Marcos,

Sure. I'll have Amy coordinate it. Amy, can you find a time for us? Thank you.

Hi Rakesh,

Can we do a walk through of your O'Reilly presentation when you have time?

Cc: amy @ x.ai
One Email + Click

Rakesh xcotai <rakesh.chada@human.x.ai>
to Marcos, Amy

Hey Marcos,

Sure. I’ll have Amy co-ordinate it.

Amy

Can you find a time for us? Thank you.

Regards,
Rakesh.
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*DS* = Data Science
*DL* = Deep Learning
High Level Product Architecture

- Incoming Emails
  - Pre-processing (Parsing etc)
  - Entity Extraction
  - Intent Classification
- Composer
- Outgoing Emails
- Calendar Invites

NLU = External Services
Amy's Brain

High Level Architecture
Hi Amy,

Could you please find a time for us to meet for 45 minutes in my office next week (after Monday please).

Marcos

--

Marcos Jimenez
x.ai Data Scientist/Co-Founder
Hi Amy,

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Marcos

Marcos Jimenez  
x.ai Data Scientist/Co-Founder
Extracting named entities from text

Marcos Jimenez

to Amy, Laniey, Matt, me

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Marcos

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Marcos Jimenez

x.ai Data Scientist/Co-Founder
High Level Architecture

Understanding intent from the e-mail text!

Incoming Emails

Preprocessing

Entity Extraction

Intent Classification

NLG

Composer

Outgoing Emails

Calendar Invites

Inbox

Outbox

Scheduler

Composer

NLG

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Marcos

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Marcos Jimenez
x.ai Data Scientist/Co-Founder

Schedule a new meeting!
Amy Ingram <amy@x.ai>
to me

Hi Rakesh,

Happy to get something on Marcos's calendar.

Does Wednesday, May 4 at 2:00 PM EDT work? Alternatively, Marcos is available Wednesday, May 4 at 3:00 PM EDT or Tuesday, May 10 at 3:00 PM.

Marcos's office is at 25 Broadway, New York, NY 10004, USA.

Amy

Amy Ingram | Personal Assistant to Marcos Jimenez Belenguer
An artificially intelligent assistant that schedules meetings by x.ai
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CC: amy@x.ai
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NLU challenges - meeting scheduling

- Many expressions of entities/intents exist.
  - “1/21,” “July ‘18,” “weekend,” “lunch,” “couple of days,” etc.
  - Expressions sometimes have modifiers attached to them!
    - “After the weekend,” “next Tuesday,” “early morning,” etc.
- Context plays a key role!
  - “Amy - Can you schedule this meeting for late afternoon?”
    vs
    “Amy - I will be late to the meeting.”
NLU challenges - meeting scheduling

- Entity resolution (converting to a structured representation) can be challenging.
  - “Schedule a meeting in the morning at 10 am next wk Mon-Wed”
    - We built a sophisticated parser to accomplish this!
- Identifying relevance to meeting scheduling can be hard
  - “I just got back from San Francisco yesterday.”
- Relevant meeting information is sometimes embedded inside a large body of text. The algorithm needs to learn to filter the rest of the info.
NLU challenges - meeting scheduling

- Composition challenges - Information spread in different parts.
  - “Next week works. I am busy this week though. We can try Tuesday.”

- Handling ambiguity in intents. Tracking dialog state can be helpful.
  - “I will be in London next week” can be a positive acknowledgment if the meeting is happening in London.

- Some tasks require identifying relationships between entities
  - “Amy, Please work with John, James’ assistant to get a meeting scheduled.”
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Evolution of our models

Rule Based Models
Evolution of our models

- Rule Based Models
- Third Party Library outputs
Evolution of our models

- Rule Based Models
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- Non Deep Learning models Trained In-house
Evolution of our models

Rule Based Models

Third Party Library outputs

Non Deep Learning models Trained In-house

Deep Learning models Trained In-house
Evolution - Case Study

Time Detection - Extracting time mentions from text
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- Regular Expressions
- Stanford CoreNLP, suntime etc
- Conditional Random Fields (Factorie)
- Convolutional Neural Networks (CNNs)
Evolution - Case Study

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CNNs for Time Detection

- Our new architecture based on the seminal paper “Natural Language Processing (almost) from Scratch” by Collobert et al.,

- Great results even with zero feature engineering!

- Outperformed the previous model based on CRF by a good margin.

- Simple but an effective **context-window** based approach.
  - “2 pm works for me.” => context-window(for, 3) = [“works”, “for”, “me”]
CNNs - Architecture

1. Tokens
2. Embeddings
3. Context Windows
4. Convolution & Max Pooling
5. Softmax
Word embedding visualization
Word embedding visualization
Word embedding visualization

Evolution
Word embedding visualization
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Case Study - Intent Classification

Intents

E-mail Intents

“Amy, can you cancel this meeting?”

Entity Intents

“Wednesday at 2 pm doesn’t work. But 5 pm works.”
Email Intent classification

- Non deep-learning models
  - N-grams + non text features
  - Classifier chain ensemble - Based off a research work by Read et al.,
  - Our implementation open sourced to scikit-learn!
  - SVMs, Random forests, Gradient Boosting (XGBoost FTW!)

- Deep learning models
  - LSTMs/GRUs with pre-trained word embeddings + context
  - Performance improved with data but still just on par with the non deep learning model!
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Entity Intent classification

- Non deep-learning models
  - “Context window” n-grams
  - SVMs, Random forests, Gradient Boosting etc
- Deep learning models
  - Pre-trained word embeddings initialization seemed beneficial.
  - Bi-directional LSTMs/GRUs sequence labeling architecture.
  - Better performance than its non deep-learning counterpart!
Entity Intent classification

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Bi-LSTM Sequence Labeling

Input*: 2 pm works but 4 pm does not

Non DL vs DL models

*Credits to Saeidi et al.
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Things we learned

● It is helpful to analyze the problem well beforehand and start with simpler solutions.
  ○ Based on the problem type, one solution might be more effective compared to other.
    ■ DL for Email vs Entity intent classification was one such example.
● In a supervised setting, it is helpful to analyze model’s performance as a function of number of labeled data points (Learning curves)!
  ○ Data Annotation comes at a (high) cost. Performance could already have plateaued.
Things we learned

Reference: Sentiment Neuron Analysis
Things we learned

- Invest at least as much time in designing metrics as you would in designing training algorithms!
  - A poor model might not look so under a poor metrics system! A good model might!
  - It is also helpful to think of metrics in terms of impact on the product!
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