



Enterprise AI

The importance of text

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Who are we? Why are we here?

Our company - ServiceNow

**We make the world of work,
work better for people.**

Works for you

NYSE: NOW

~6,700 Global Employees across 27 Countries

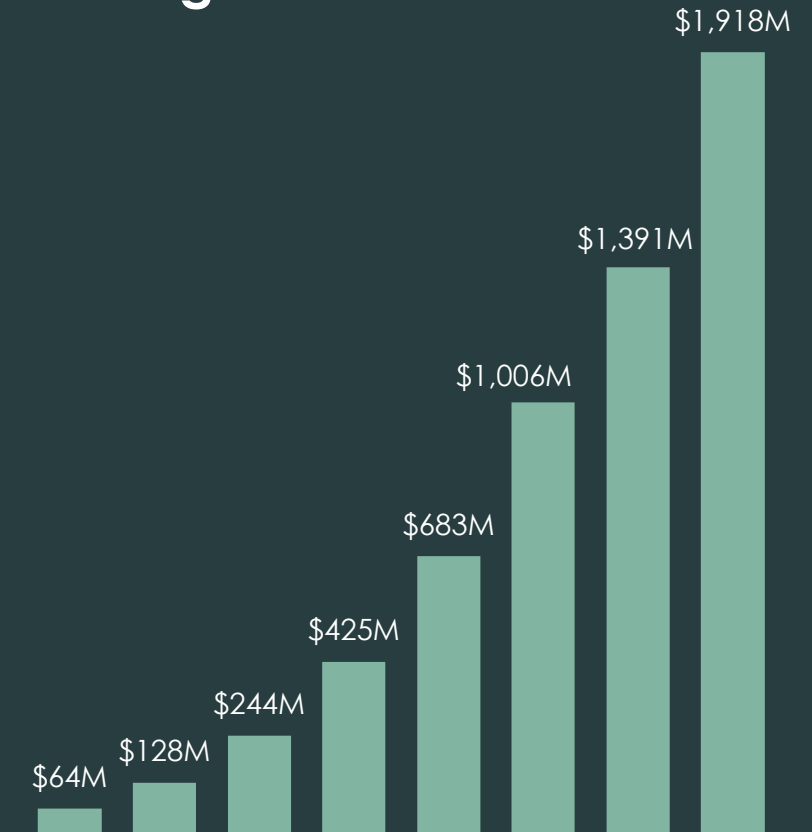
9 Pairs of Data Centers

Major Sites

Santa Clara, San Diego, Hyderabad,
London, Amsterdam, Sydney, Seattle, Tel
Aviv, and now **Chicago**



Strong Revenue Growth



Note: 606 metrics stated for FY16 and beyond

Our customers - a sampling



Great enduring companies

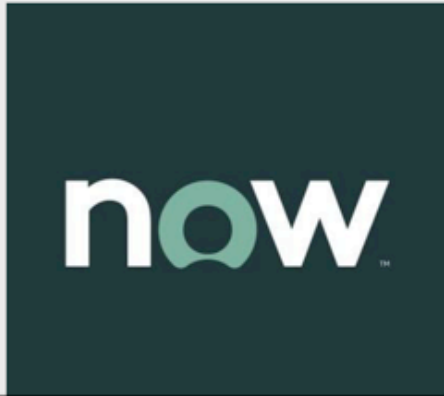
They are
purpose driven

Innovation and
execution

They invest in
talent

Exhibit “will to
fight”
and “will to win”

Innovation - the company we keep, and we are #1



#1 ServiceNow



#2 Workday



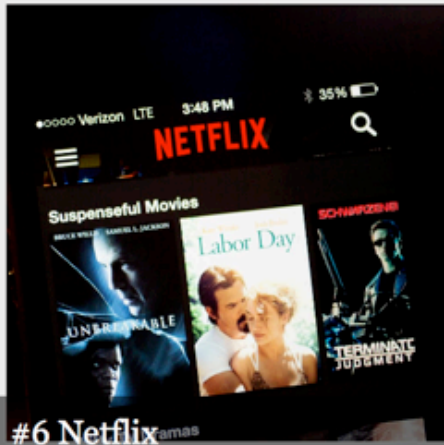
#3 Salesforce.com



#4 Tesla



#5 Amazon.com



#6 Netflix



#7 Incyte



#8 Hindustan Unilever



#9 Naver



#10 Facebook

Priority: Develop talent - we are hiring in Chicago

Machine learning engineers

UI/UX engineers

All levels, and experience

What do we “Product” folks do?

Why AI using unstructured textual information is important

Emerging products



Security



Customer Service



HR

IT products



ITSM



ITOM



ITBM & ITAM



User and Service
Experience



Now Platform™



Service Intelligence

The Now Platform scale

Production instances

~7,500



Customer transactions per month

~12 Billion



licensed users

~18 Million

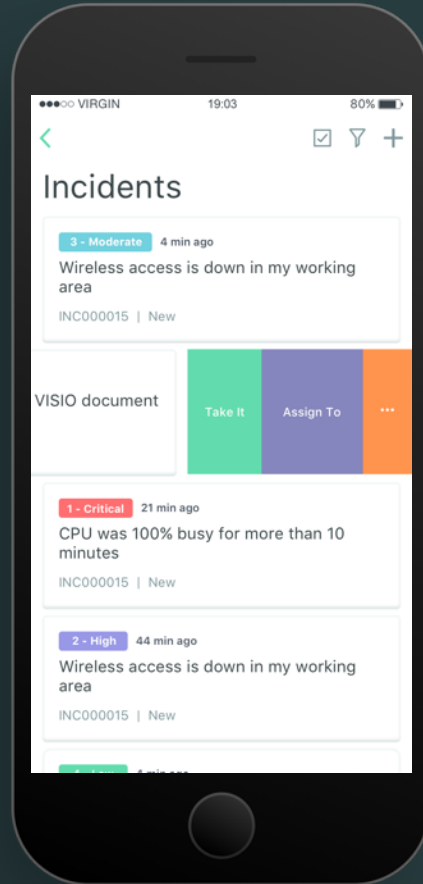


of Cloud API calls per month

~18 Billion

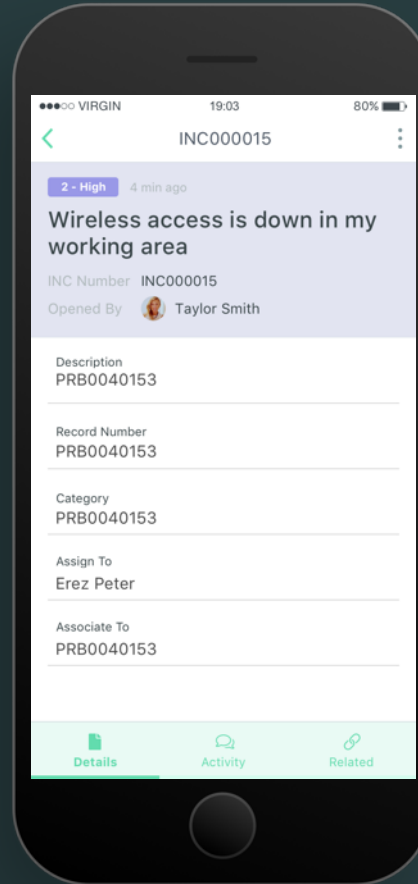


Native mobile applications



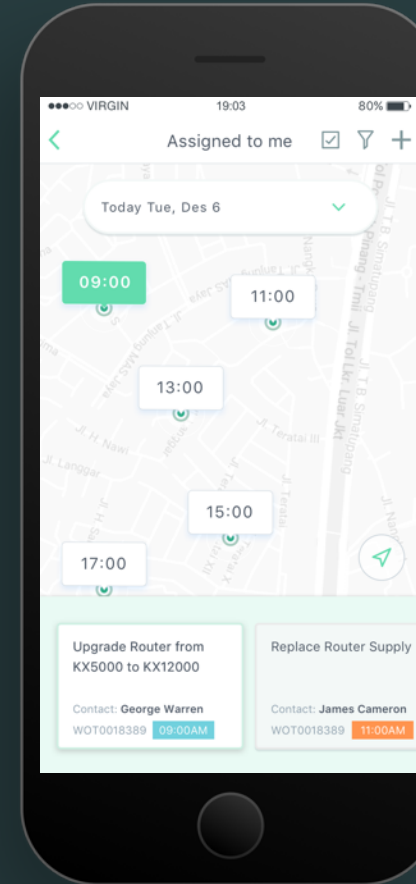
Incidents

Swipe Actions



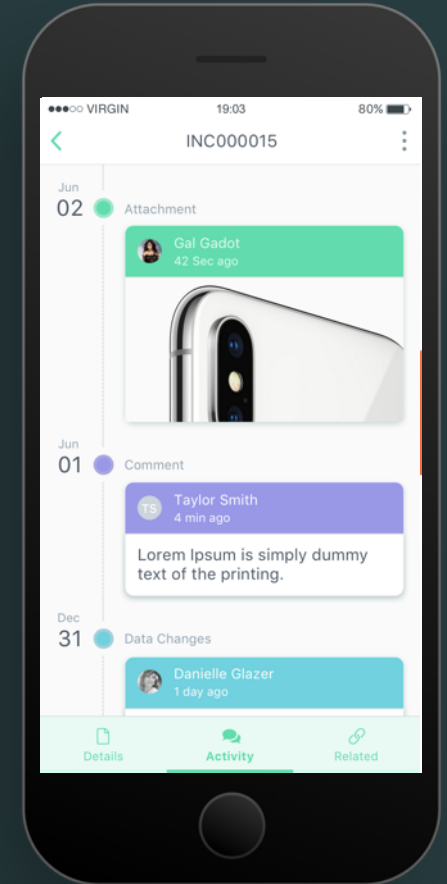
Incidents Details

Call/Text/GPS



Map View

Filter by Time/Location



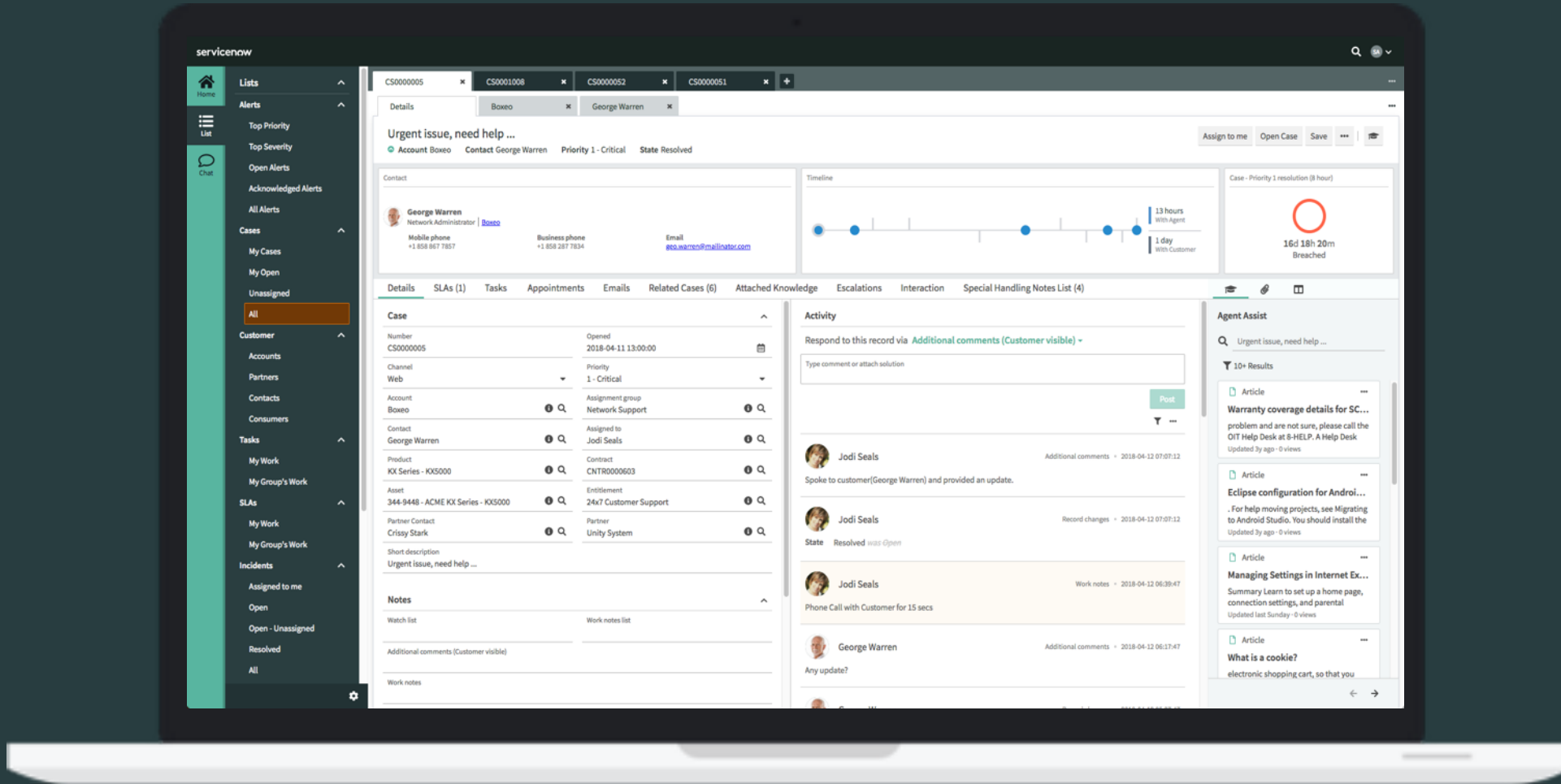
Activity Stream

Add Attachments,
Images, Comments

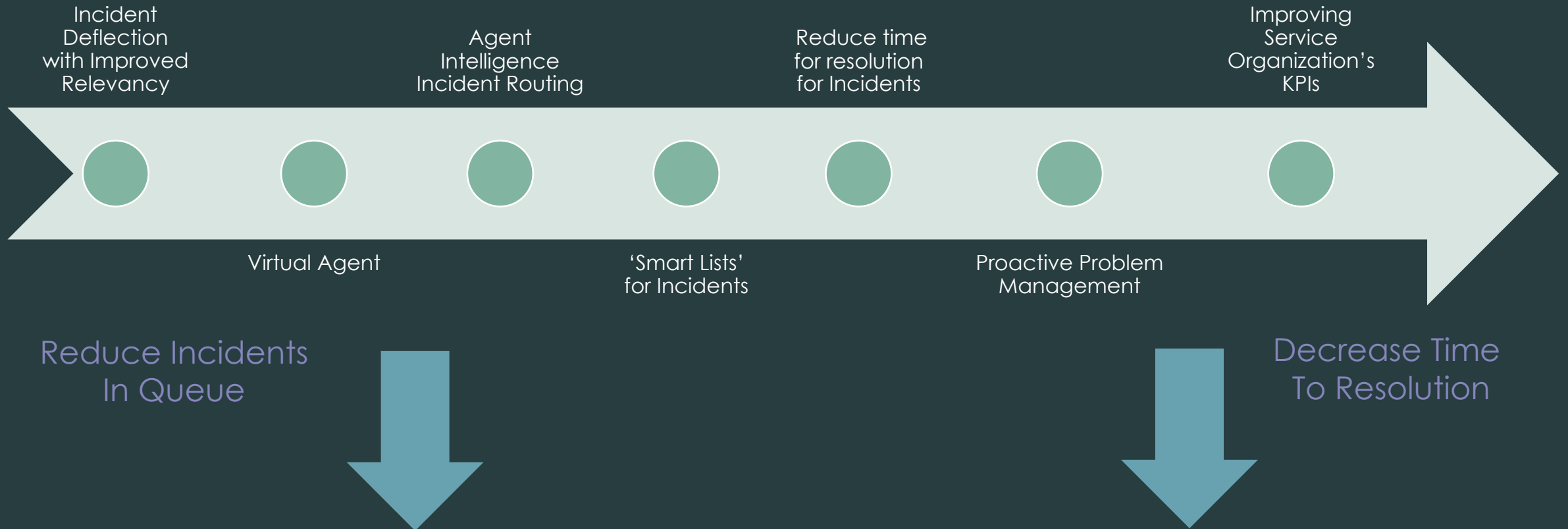
Virtual Agent



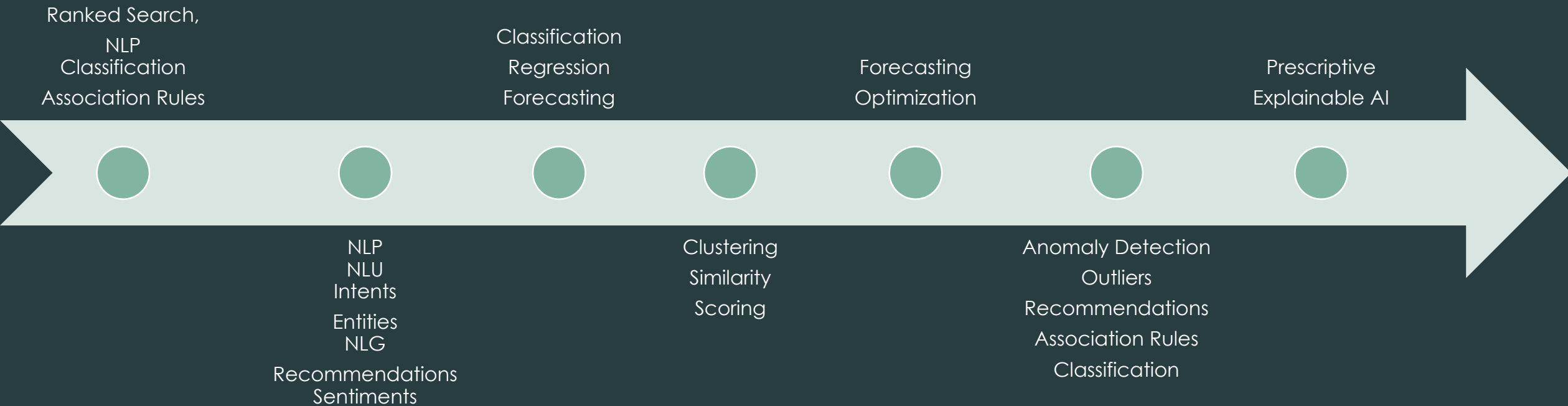
Agent Workspace



Opportunity for AI driven service experience



An AI framework drives it all!



Hence, the importance of AI using text in the enterprise

- **Enterprise** very different from **Consumer** (ServiceNow data \neq Twitter data)
 - Consumer apps have **one** big **database** of text to study and build models from
 - Enterprise has security rules: we have **5k+** customers all in **separate instances**
 - Challenge is to **build many** similar **models** on **different datasets** with expectation that they work **OOB**
- Language “at work” is different from language “at home”
 - Word embedding (eg from Google) on “home” language don’t capture work jargon (NER is hard)
 - **URLs**, file directory **paths**, product **versions** – all potentially meaningful, but **inflate vocabularies**
 - “Sentiment analysis” research not on point. “**propensity to escalate**” matters rather than “**negative**”
 - **Many** contemporary chatbots are working to a “keep the conversation going” metric, **longer is better**
 - **Customers** seeking support/answers **want FACTS** and **ACTION**, not chit-chat. **Shorter** is better.
 - I can ask IT for a new laptop, but am I allowed to have one? Can we **blend rules/logic with NLP** effectively?
- We cover multiple **domains** (HR vs IT), and many ‘**subdomains**’ (IT but at different customers)
 - **Transfer** learning or **meta-learning** techniques should be relevant
 - Learn **inductive biases** to pick up customer’s jargon. **We know it’s an IT shop**, just learn local vocabulary.
 - Combine Knowledge Base + NLP? **NER** plus **relations**: team X in org Y working on project W for release Z

Volume and Variety

Incidents: short to medium text

Customer	Yearly Volume
A	673K
B	426K
C	187K
D	187K
E	171K

Alerts: short to medium text

Customer	Yearly Volume
A	9.6MM
B	1.8MM
C	380K

Knowledge Base: medium to large text

Customer	Yearly Volume
A	160K
B	131K

Class of scaling problems

Effective methodologies for combining hierarchical data

Incident records have data at different levels

Description is a low-level feature.

Category or other tags is a higher level feature.

Need to combine high and low level features.

Text matching under varying text lengths

A new incident may have a pre-existing resolution in an article in the knowledge base. How to find the best one?

Incident description is a short text

KB articles are long texts.

New methodologies needed for short-to-long text matching.

Vector representations of text for deep learning models

Text data can be represented many different ways: TF/IDF vectors, paragraph vectors, word vector based convolution, etc.

Determining the best representation.

Combine generic word2vec/glove vectors and customer/domain specific vectors to get higher precision

Get these things to work across languages scalably

Challenges with ML/AI solutions

Encapsulation is more difficult in ML solutions

Changing anything changes everything (CACE)

Data dependencies more severe than logic dependency

Common anti-patterns

Real systems = 5% ML Code + 95% “glue” code

Pipeline jungles

Testing is much more complex

Exact reproducibility, the backbone of traditional testing can be often compromised

Multiple Languages as in English, French etc

Enterprise Specific Language

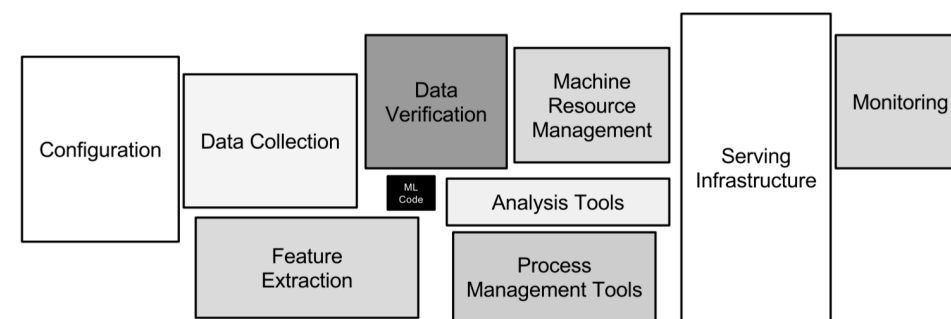


Figure 1: Only a small fraction of real-world ML systems is composed of the ML code, as shown by the small black box in the middle. The required surrounding infrastructure is vast and complex.

Source: Sculley, et al NIPS 2015

Many other challenges remain

Need too many 'labeled' examples.

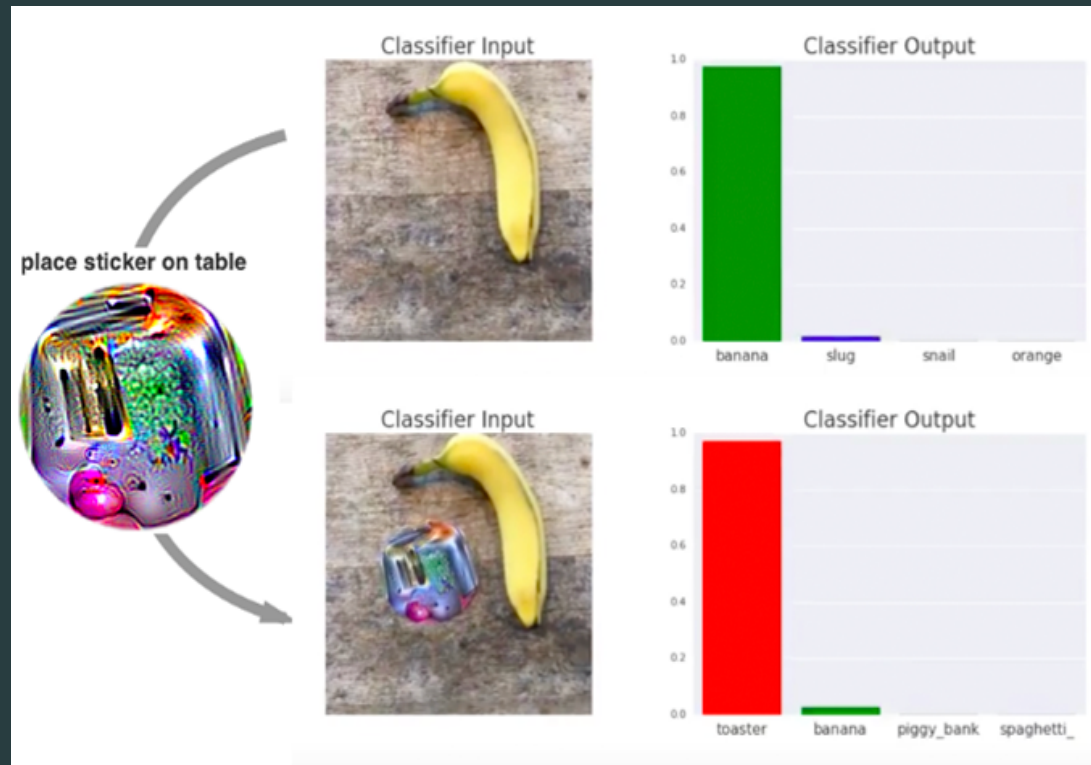


How does the math (SGD) work here?

Many other challenges remain

Easy to manipulate models

Difficult to explain



Why ServiceNow!

AI is the key
differentiator

Enterprise AI is lot
about text

And, we have fun
being a guiding
hand to each
customer one at a
time



Thank you!