Fantastic Problems

And Where to Find Them

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Senior Data Scientist_

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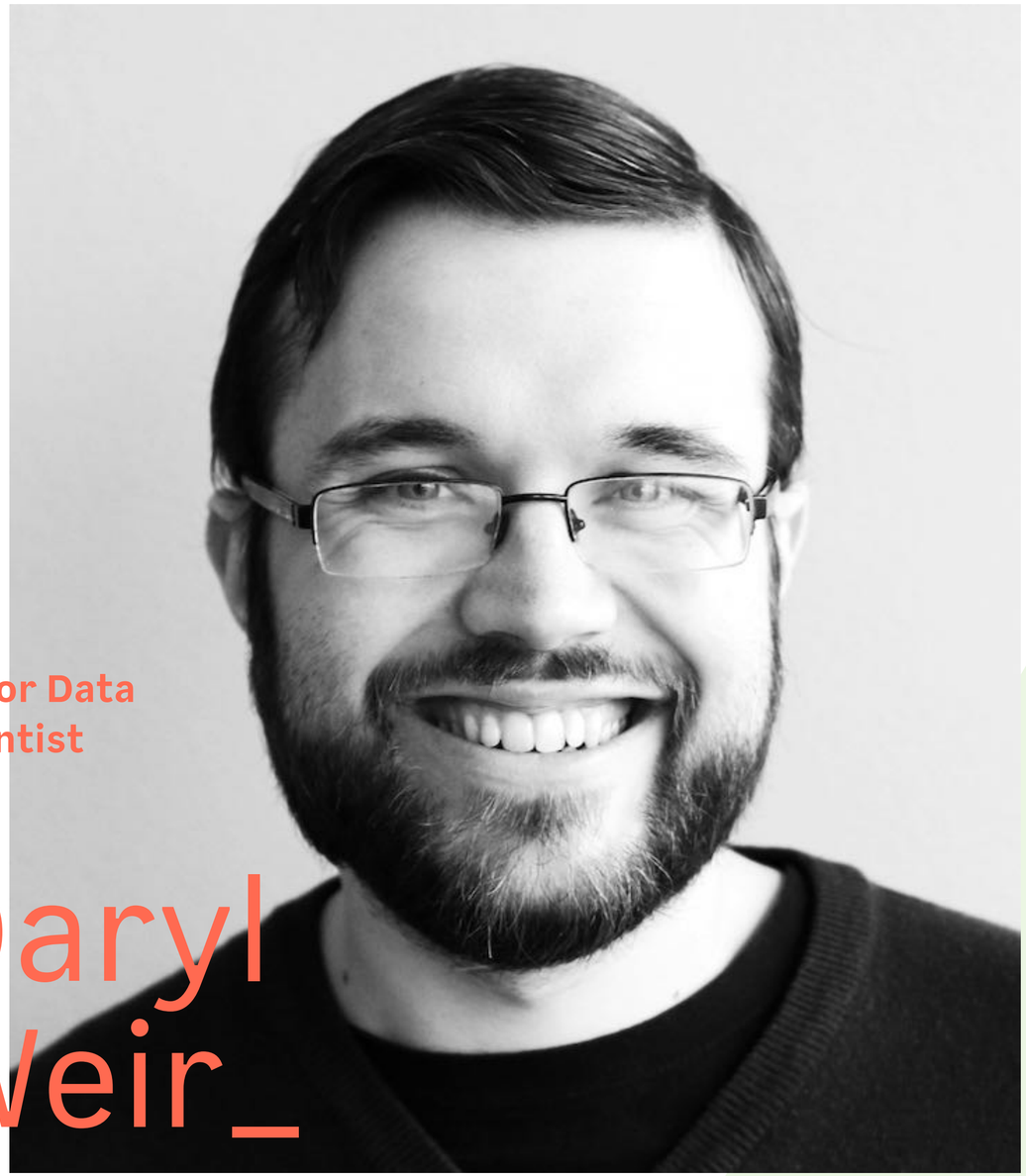
400+ employees from 22 countries

8th year in a row profitable growth

YOY growth 30%



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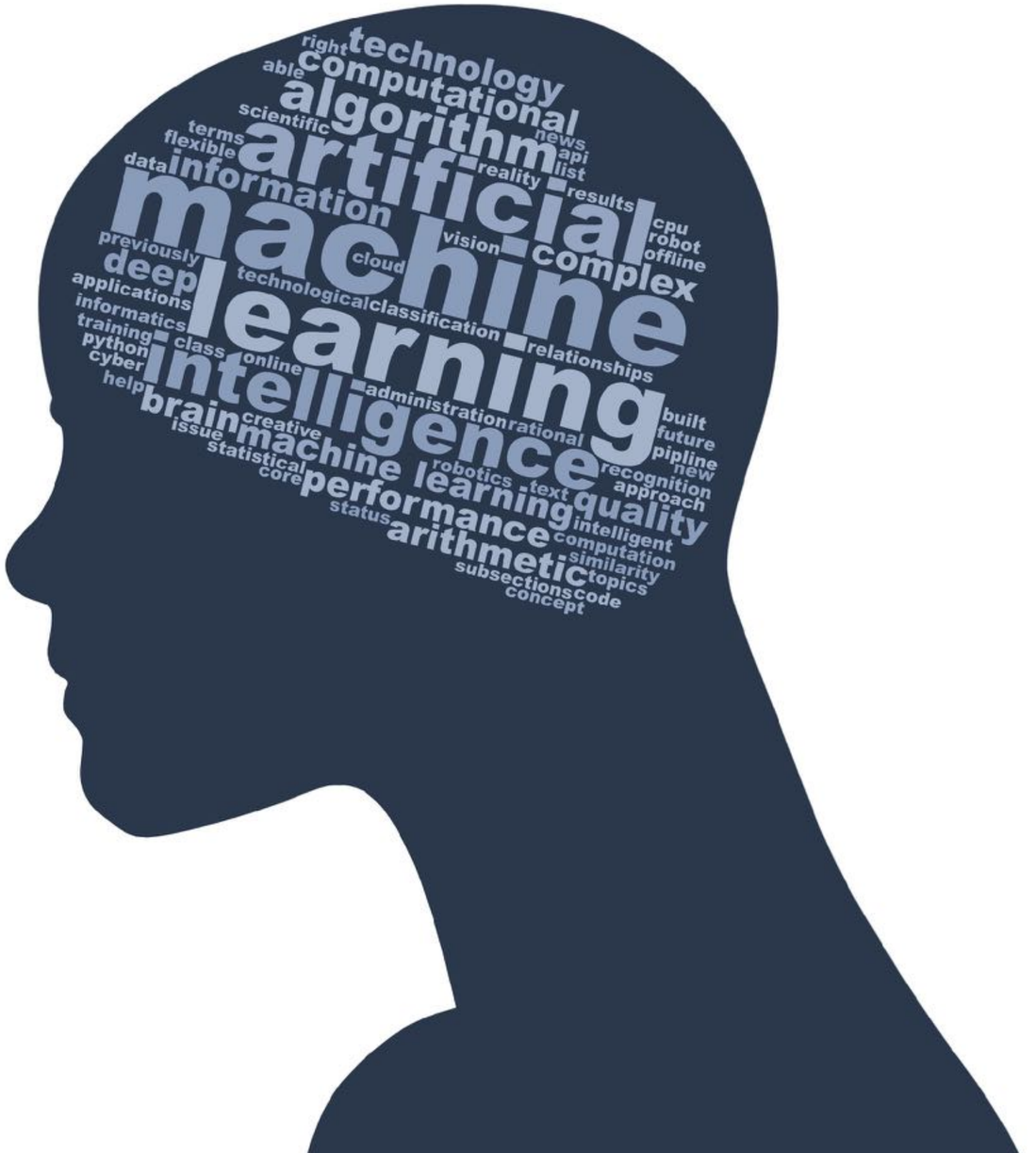
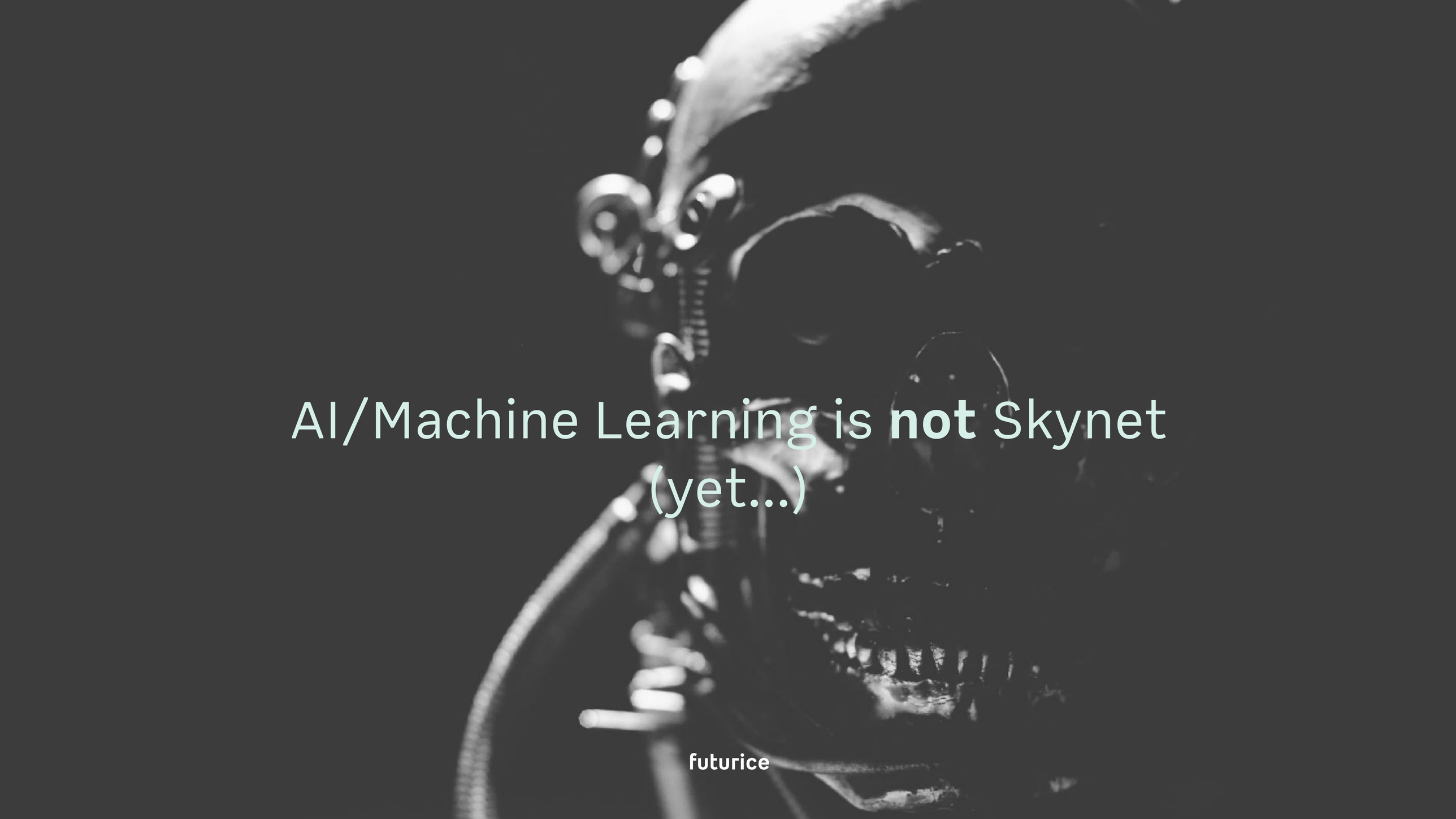
Machine Learning Hype_

AI, big data, machine learning... These have been buzz words for years now

This talk tries to answer two key questions:

- **What can machine learning actually do?**
- **Should I use machine learning to solve my problem?**




AI/Machine Learning is **not** Skynet
(yet...)
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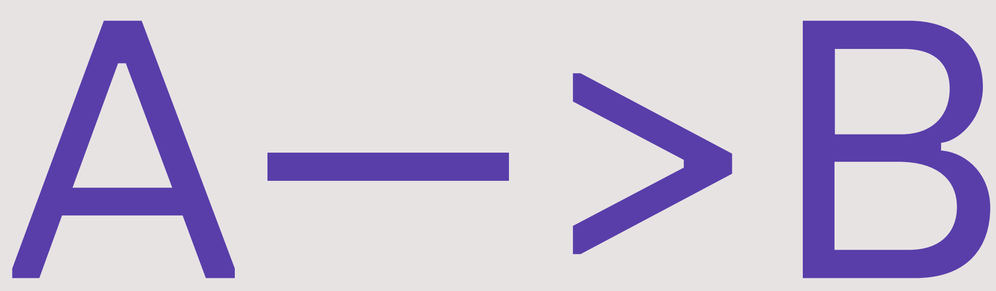
So what is it?_

Machine learning is really good at **answering narrow questions**

It does this by **learning from examples**

The most common method is **supervised learning**, where problems look like:
Given some **input A**, predict an **output B**

By choosing the right A and B, you can do some amazing stuff



For example_

Baby’s first self driving car

Narrow question: given the road looks like this, how should I turn the steering wheel to not crash?

Input: camera image of the road
Output: steering wheel angle

(CMU did this in 1995 - the car drove 3000 miles across the US)

But what kind of problem should we look for?_

“If a typical person can do a mental task with less than one second of thought, we can probably automate it using AI”

- Andrew Ng

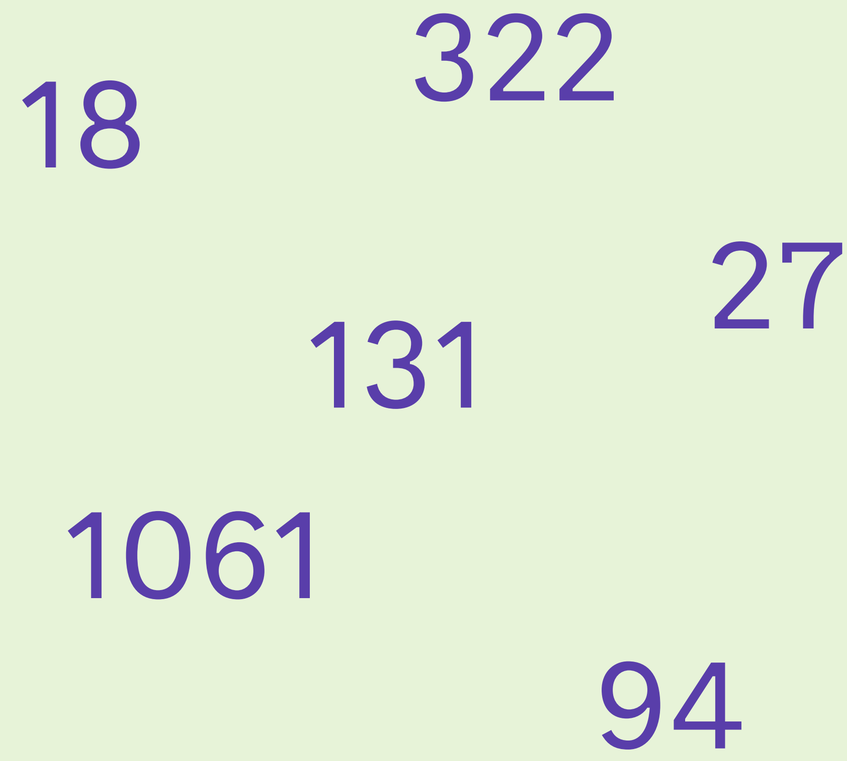
A (somewhat trite) counterexample_

Are these numbers **odd** or **even**?

You can (hopefully) judge this in under a second

But many popular machine learning algorithms are **terrible** at learning this (from the numbers alone)

Not all problems that **can be** tackled with ML **should be**



My rule of thumb_

You might have a machine learning problem if:

1 - writing down a set of rules is hard

BUT

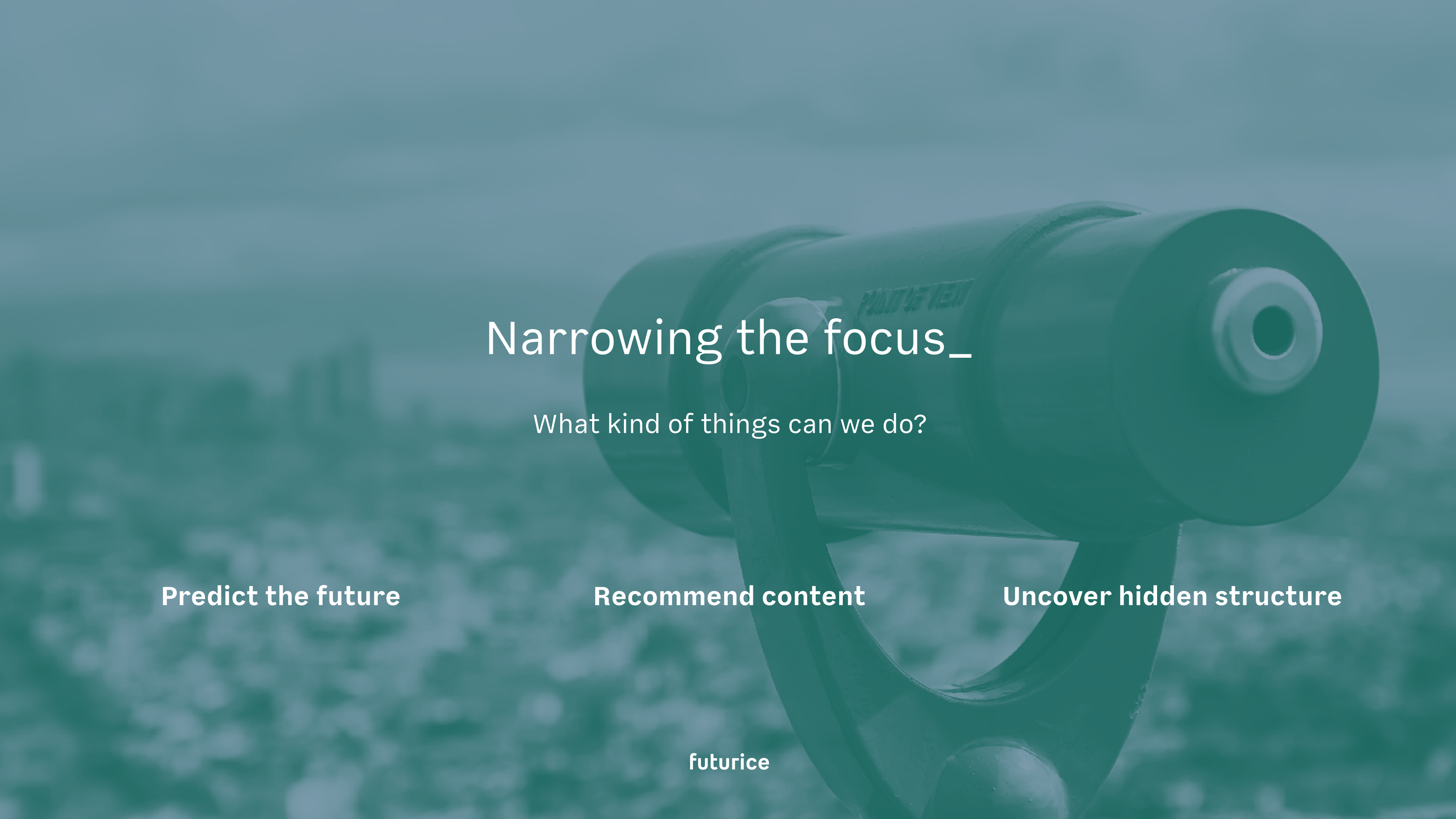
2 - gathering examples is easy

Is there a cat in this image?_

Writing rules for the presence or absence of a cat is really, really hard

BUT

Finding cat pictures is really, really easy



Narrowing the focus_

What kind of things can we do?

Predict the future

Recommend content

Uncover hidden structure

Predicting the Future_

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Scenario_

We have lots of historical examples of system state, each one labelled by its outcome

Given a new example of the state, we try to predict the outcome

Such problems fall into two main types: **regression** and **classification**

Regression problems are those where the outcome is a number, for example:

— how many potatoes will my supermarket sell next week?
— what's the optimal price to sell this stock?
— what speed should I drive given the weather & traffic?

Classification problems are those where the outcome is one of a fixed set, for example:

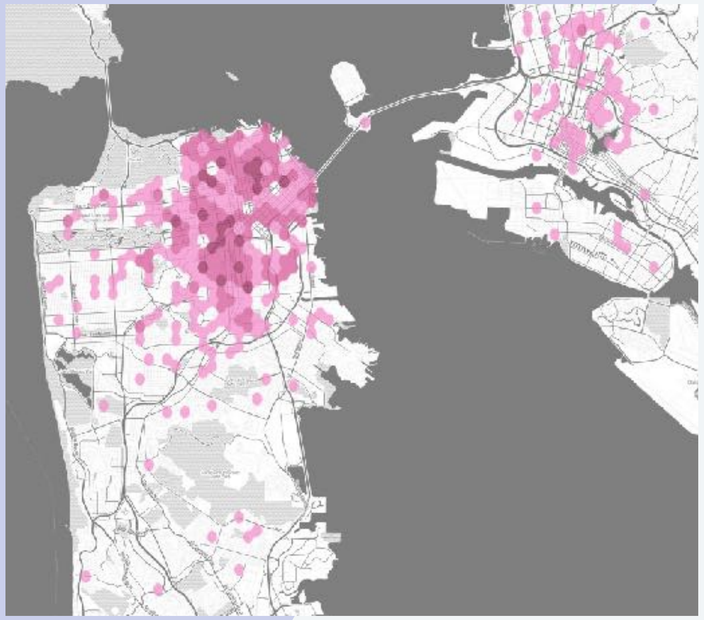
— whose face is in this image?
— is this credit card transaction fraudulent?
— do these scan results indicate cancer?

Case: AirBnB_

AirBnB is a great example of a company oriented around data

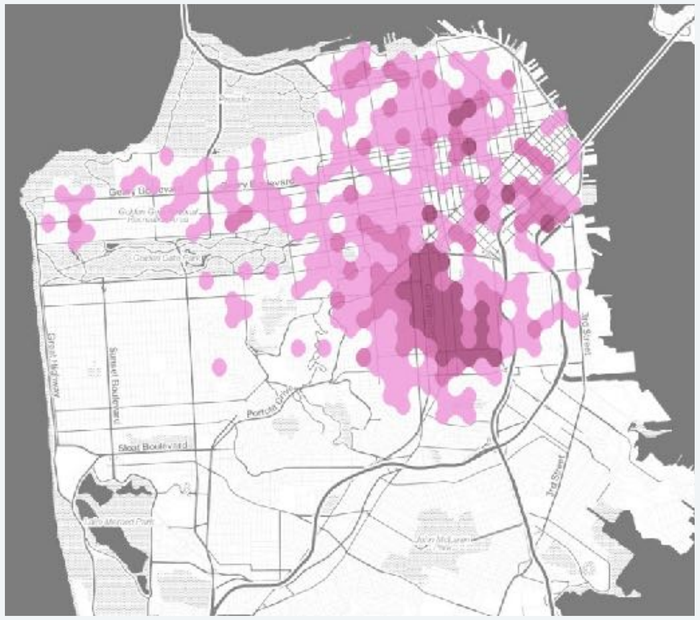
They blog regularly about data science and open source some of their tools

One problem they've talked about: given the user's search term, **should we show a given listing in the results**?



Basic distance based search for San Francisco shows many rentals in Oakland

Users were likely to find these results irrelevant



Bayesian model estimates the probability of booking each listing given a specific search

This sped up the booking process and significantly increased conversion rate

Case: Railways_

Two buzz words for the price of one: machine learning + IoT!

Modern trains and rails are highly instrumented with sensors (motion, sound, pressure, etc.)

Using data from these, we can classify whether or not a part (e.g. a wheel or door) will **fail within a given time**

Lets the operator move from scheduled to on-demand maintenance/replacement

VR Group estimates this cuts amount of wheel maintenance by around a third

Bonus inception: sometimes the sensor themselves start giving incorrect readings

Another classifier can detect these faults before they suggest phantom breakdowns

Recommending Content_

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Scenario_

Many businesses depend on content of some sort, e.g.:

– articles and videos
– products in a store
– ads

It is often valuable to personalise the content shown to your users

There are two main methods to **predict content users will like**

Content based recommenders suggest, unsurprisingly, based on the actual content

– these articles have similar topics to your previous reads
– more videos from channels you watched

But it's not always easy/ possible to define similarity between pieces of content

Collaborative filters suggest things other users have liked

The preferences of others are weighted by how similar they are to you

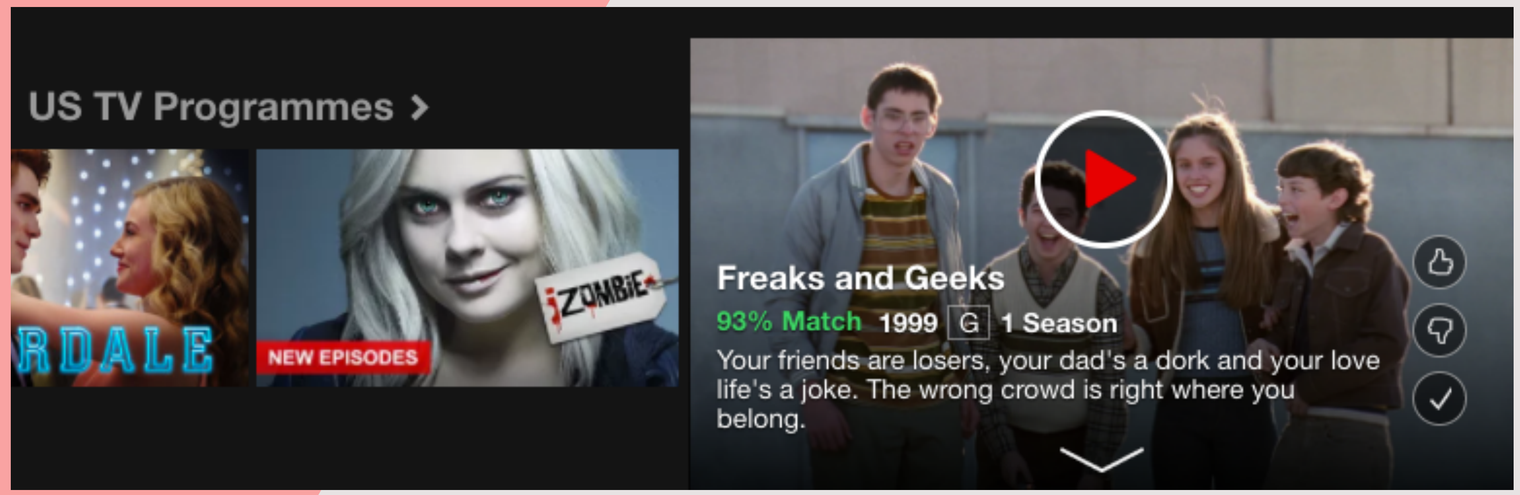
– "Customers also bought..."
– Spotify Discover Weekly

Case: Netflix_

Netflix is one of the most well known users of recommender systems

Like AirBnB, they blog regularly and have some open source tools available

Good recommendations increase user satisfaction, encourage continued use, and drive users to the ‘long tail’

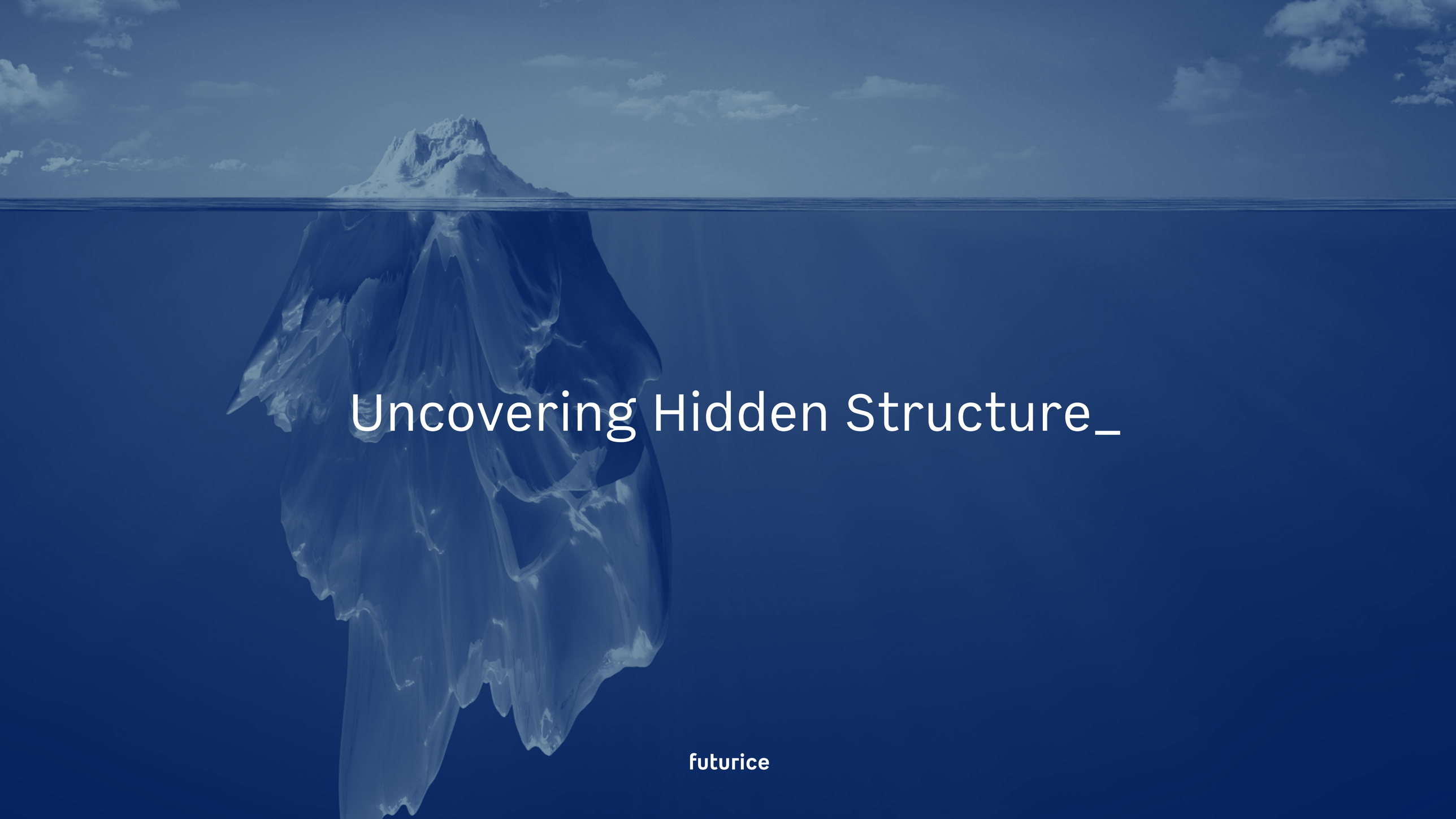


Recently changed from star based ratings to a thumbs up/ down system

Better UX, avoids differences in users’ rating systems

Famously offered a $1M prize to anyone who could improve their recommender by 10%

Winning solution was never used!



Uncovering Hidden Structure_

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Scenario_

What if we don’t have labels for our historical states?

Another major ML application area is automatically detecting recurring patterns in data

This is called **unsupervised learning** - it’s about learning what’s interesting about some given data

This lets us ask different sorts of questions, like:

— how do players of my game **group together** based on play behaviour?

— is this spending behaviour **unusual** given someone’s past purchases?

— what are the **common topics** in this collection of documents?

Case: Google News_

Google has been very vocal about its transformation into “a machine learning company”

As of 2016, ~10% of their engineers have ML experience and internal training is growing

They have stated a goal of systematically applying machine learning in all their business areas

Google News automatically groups versions of the same story from different outlets

Stories are also grouped to form news categories

The rankings of different topics and outlets can be tailored by the user explicitly

The service can also learn user preferences from usage data

Trying it out_

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Starting out with ML_

Excellent tooling - try the Anaconda distribution

Jupyter notebooks allow mixed code and Markdown

Can be slow

Designed with data analysis in mind

Amazing library and community support

Not general purpose

Only for masochists

The real third option_

Excellent tooling - try the Anaconda distribution

Jupyter notebooks allow mixed code and Markdown

Can be slow

Designed with data analysis in mind

Amazing library and community support

Not general purpose

Fast, powerful language with excellent support for really big datasets (via Spark, Hadoop)

Highly parallel

Not very beginner friendly

Resources_

“I want tutorials and interesting blog posts pitched at beginners (and I don’t mind Python)”

github.com/hangtwenty/dive-into-machine-learning

“Python sucks, show me resources for machine learning in <my language of choice>”

github.com/josephmisiti/awesome-machine-learning

“Coding sucks, I just want to read a book”

‘The Master Algorithm’ by Pedro Domingos

If you remember 3 things_

1) Machine learning answers narrow questions
2) Look for complex rules with plentiful examples
3) Don’t use Matlab

Thanks for listening!

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