Use case definition

Sprint 1 - Week 1

INFO 9023 - Machine Learning Systems Design

2024 H1

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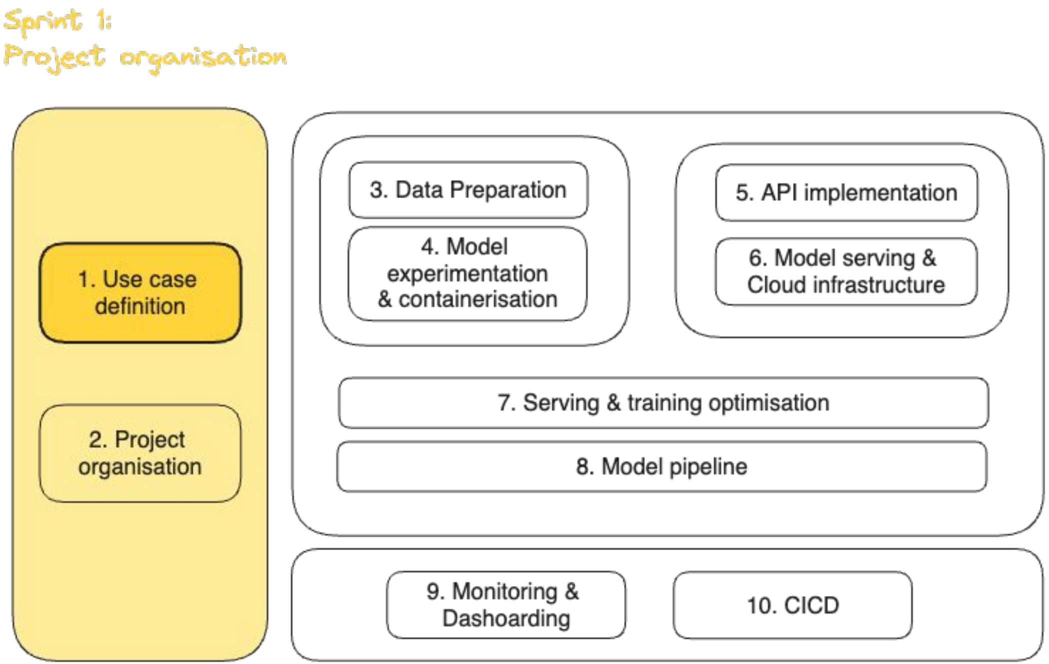
Status on our overall course roadmap



Agenda

What will we talk about today

Lecture (2 hours)

1. Use case deep dives
2. Project phases & challenges
3. Project definition framework

- Bonus: Explainable AI (XAI)

Use case deep dives

Real-estate valuation assistant

Context & Problem Statement

…heard of Fednot?

Fednot

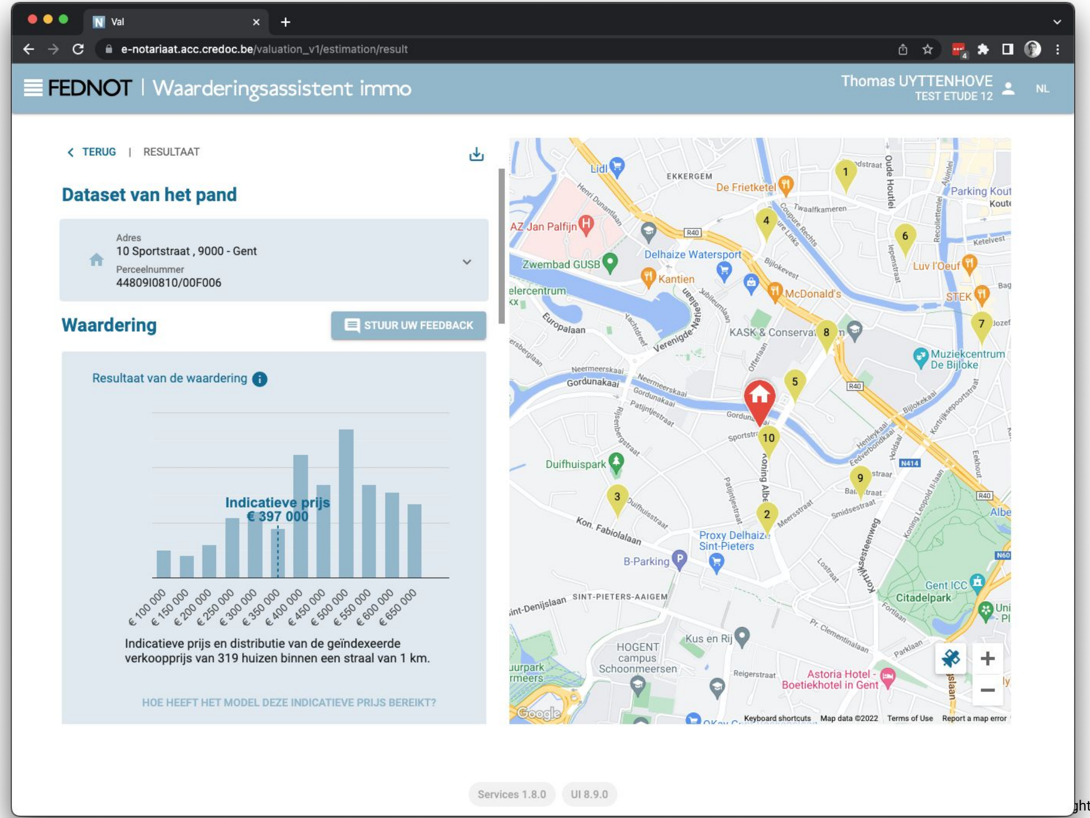
= Koninklijke **Fed**eratie van het Belgisch **Not**ariaat

= **Féd**ération Royale du **Not**ariat belge

= Royal **Fed**eration of the Belgian **Not**aryship

Fednot supports the notary studies with juridical advice, office management, IT solutions, trainings, and information for the general public.

Valuation assistant.



How the ML model conceptually works

Known values that the model will use as input to make predictions

Feature variables

What the model needs to predict

Target variables

Single house

Train set

Test set

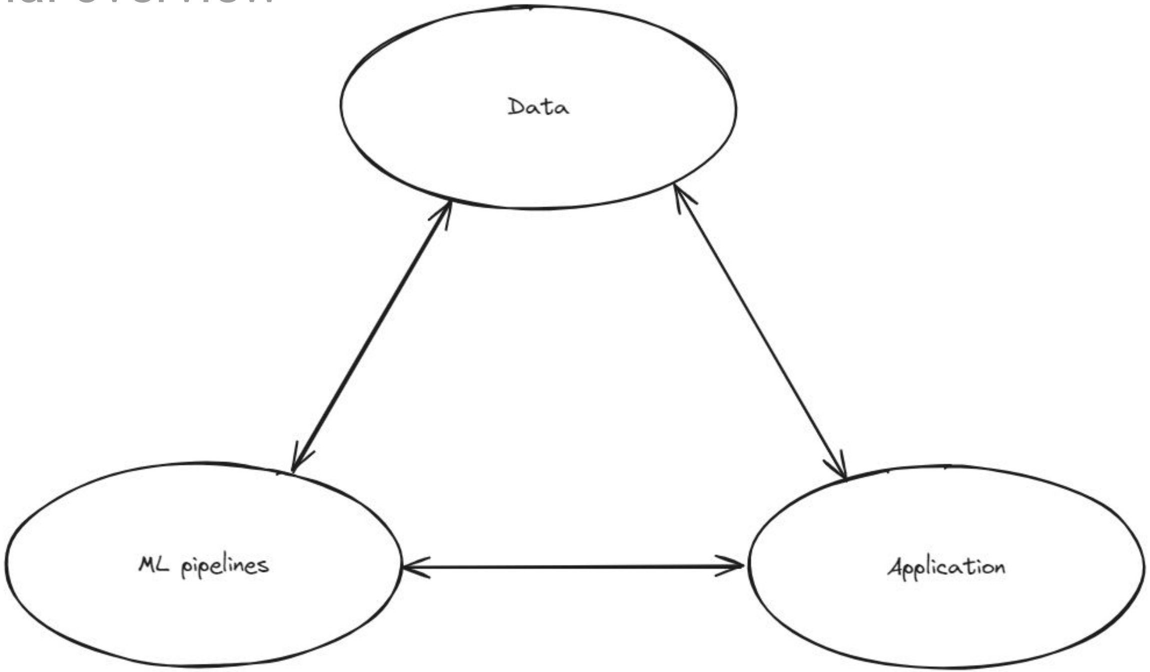
ID	Size (sqft)	Bedrooms	Bathrooms	Distance to City Center	Garage	House Price (k$)
1	2200	3	2	5	Yes	300
2	1800	4	2	3	No	275
3	1400	2	1	10	Yes	200
...	...	...	...	...	...	...
80 000	3000	5	4	4	Yes	400
80 001	1600	3	2	12	No	? (Test)
...	...	...	...	...	...	...
100 000	2100	4	2	6	Yes	? (Test)

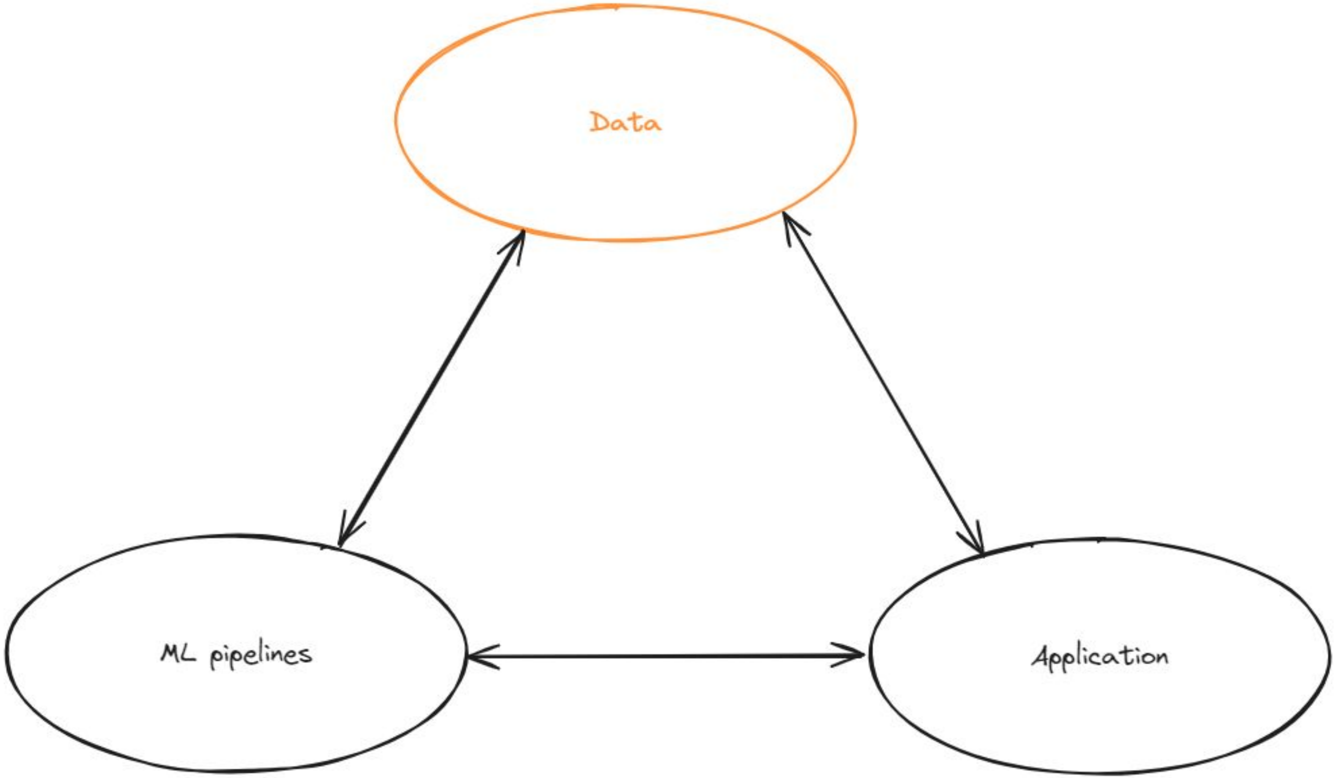
The ML model will see many **observations** (houses) defined as a set of **features** (information, variables). From it the model will learn patterns and what impacts **target variable** (house prices).

If given new observations, the model can predict the target variable based on the input features.

Solution architecture.

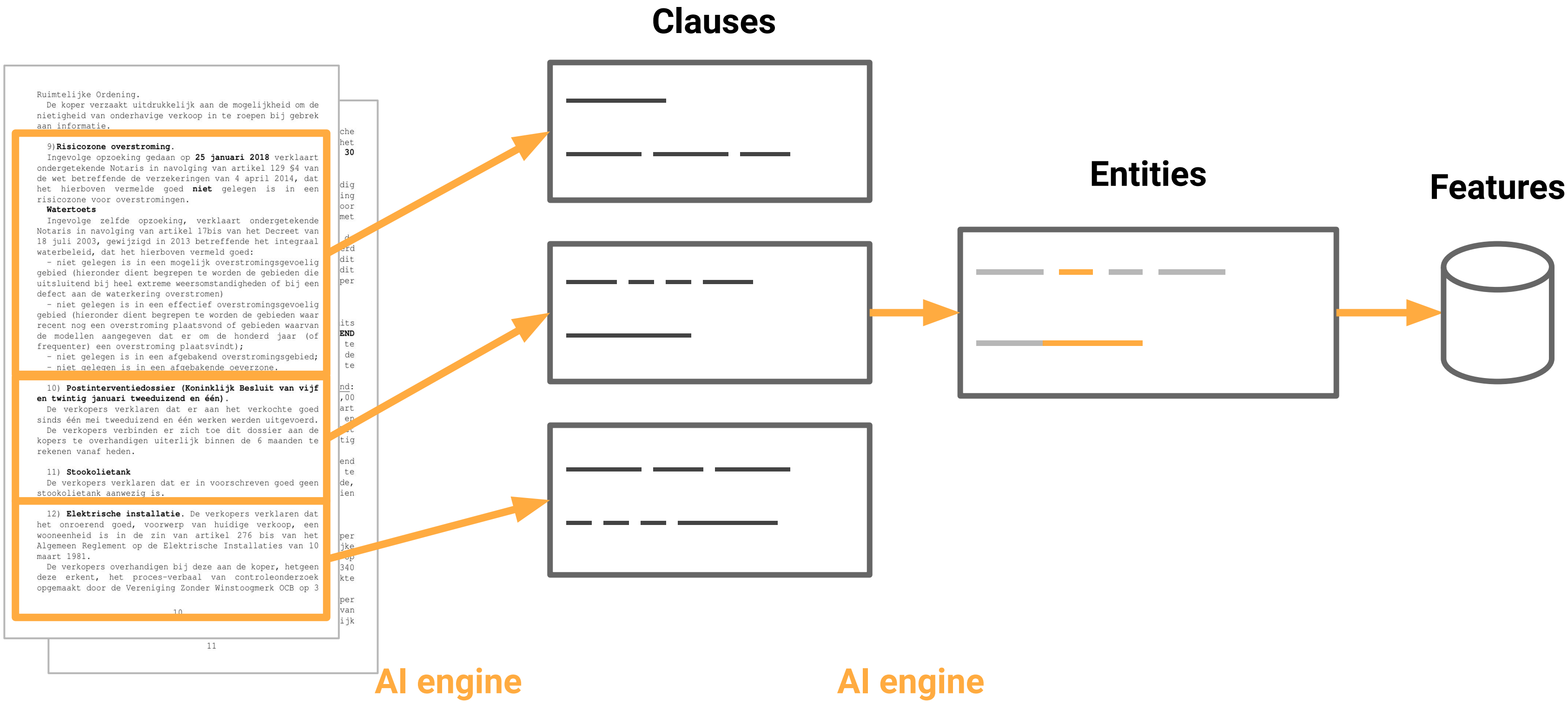
A functional overview




Data
ML pipelines
Application

Valuation features.

Starting from unstructured PDF documents



Valuation features.

Processing the texts from deeds

We want to extract named entities!

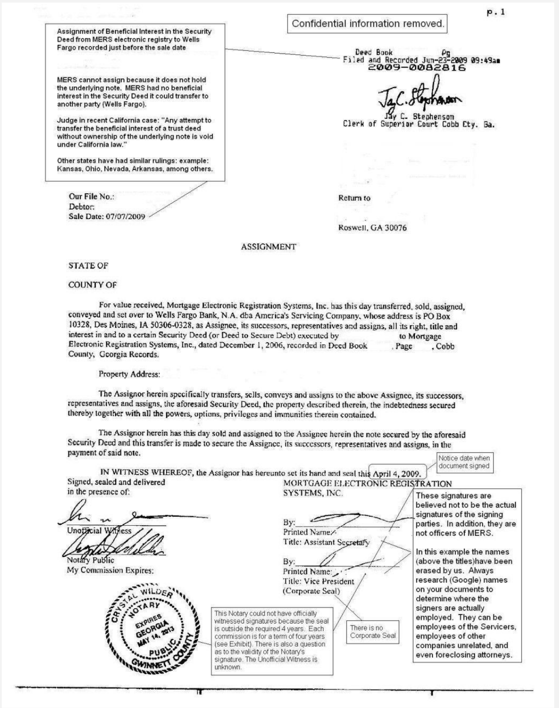
- Persons
- Dates
- Addresses
- Locations
- ...

Erfdienstbaarheden
Het goed wordt verkocht met al zijn gekende en ongekende, zichtbare en onzichtbare, voortdurende en niet-voortdurende erfdienstbaarheden en zakelijke rechten en verplichtingen.
De verkoper verklaart geen weet te hebben dat het goed is bezwaard met onzichtbare erfdienstbaarheden behoudens de erfdienstbaarheid vermeld in de eerder aangehaalde eigendomsakte verleden voor notaris Hans Deprez op 14 oktober 2012 waarin letterlijk het volgende wordt vermeld:
"Ten titel van inlichting en zonder de bedoeling exhaustief te zijn, worden de volgende erfdienstbaarheden aangehaald, zoals deze vermeld staan in de akte verleden door notaris Hendrickx te Antwerpen op 7 april 2014 overgeschreven inhoudende verkoop door de vennootschap aan de heer Peeters Tom:
"Over het verkochte goed te Stationsstraat 148 wordt onvergeld en eeuwigdurend een erfdienstbaarheid van doorgang behouden in het voordeel van het erf van de bewoner.
Deze doorgang zal mogen gebruikt worden zowel te voet als met gemotoriseerde voertuigen, om de terreinen achter de bestaande gebouwen van de verkoper en deze gebouwen zelf langs hun achterzijde te kunnen bereiken of verlaten, doch enkel in noodgevallen (bijvoorbeeld door de brandweer of andere hulpdiensten).
Om in voorkomend geval te allen tijde en ten gerieve van de aanpalende erven van verkoper de vrije doorvaart te verzekeren, zal vijf meter achter de bestaande gebouwen van verkoper, nooit enige constructie, aanplanting of hindernis mogen opgesteld worden, incluis enige obstructie ten belope van de bedrijfsuitvoering van Dynamo BVBA die hieronder omschreven staat als zijnde de primaire en op het moment van schrijven enige..."

Valuation features.

Legal real-estate data

legal document



p. 1

Confidential information removed.

Assignment of Beneficial Interest in the Security Deed from MERS electronic registry to Wells Fargo recorded just before the sale date

MERS cannot assign because it does not hold the underlying note. MERS had no beneficial interest in the Security Deed it could transfer to another party (Wells Fargo).

Judge in recent California case: "Any attempt to transfer the beneficial interest of a trust deed without ownership of the underlying note is void under California law."

Other states have had similar rulings: example: Kansas, Ohio, Nevada, Arkansas, among others.

Deed Book Pg
Filed and Recorded Jun-23-2009 09:49am
2009-0082816

Jay C. Stephenson
Clerk of Superior Court Cobb Cty. Ga.

Our File No.:
Debtor:
Sale Date: 07/07/2009

Return to

Roswell, GA 30076

ASSIGNMENT

STATE OF

COUNTY OF

For value received, Mortgage Electronic Registration Systems, Inc. has this day transferred, sold, assigned, conveyed and set over to Wells Fargo Bank, N.A. dba America's Servicing Company, whose address is PO Box 10328, Des Moines, IA 50306-0328, as Assignee, its successors, representatives and assigns, all its right, title and interest in and to a certain Security Deed (or Deed to Secure Debt) executed by to Mortgage Electronic Registration Systems, Inc., dated December 1, 2006, recorded in Deed Book , Page , Cobb County, Georgia Records.

Property Address:

The Assignor herein specifically transfers, sells, conveys and assigns to the above Assignee, its successors, representatives and assigns, the aforesaid Security Deed, the property described therein, the indebtedness secured thereby together with all the powers, options, privileges and immunities therein contained.

The Assignor herein has this day sold and assigned to the Assignee herein the note secured by the aforesaid Security Deed and this transfer is made to secure the Assignee, its successors, representatives and assigns, in the payment of said note.

IN WITNESS WHEREOF, the Assignor has hereunto set its hand and seal this April 4, 2009.

Notice date when document signed

Signed, sealed and delivered in the presence of:

Unofficial Witness

Notary Public
My Commission Expires:

MORTGAGE ELECTRONIC REGISTRATION SYSTEMS, INC.

By:
Printed Name:
Title: Assistant Secretary

By:
Printed Name:
Title: Vice President
(Corporate Seal)

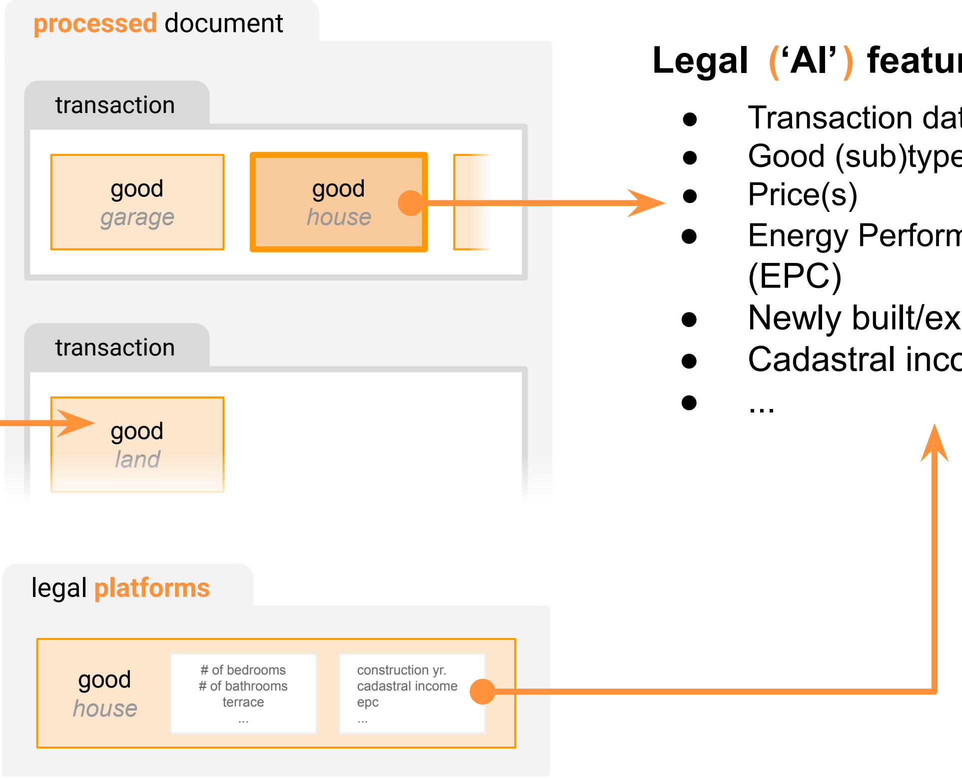
These signatures are believed not to be the actual signatures of the signing parties. In addition, they are not officers of MERS.

In this example the names (above the titles) have been erased by us. Always research (Google) names on your documents to determine where the signers are actually employed. They can be employees of the Servicers, employees of other companies unrelated, and even foreclosing attorneys.

This Notary could not have officially witnessed signatures because the seal is outside the required 4 years. Each commission is for a term of four years (see Exhibit). There is also a question as to the validity of the Notary's signature. The Unofficial Witness is unknown.

There is no Corporate Seal

CRYSTAL WILDER NOTARY PUBLIC EXPIRES GEORGIA MAY 14, 2013 GWINNETT COUNTY



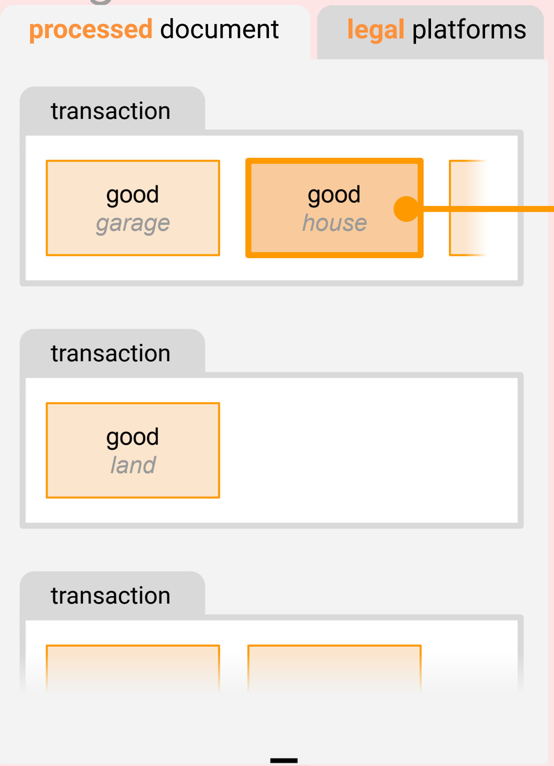
Legal ('AI') features

- Transaction date
- Good (sub)type
- Price(s)
- Energy Performance Certificate (EPC)
- Newly built/existing
- Cadastral income
- ...

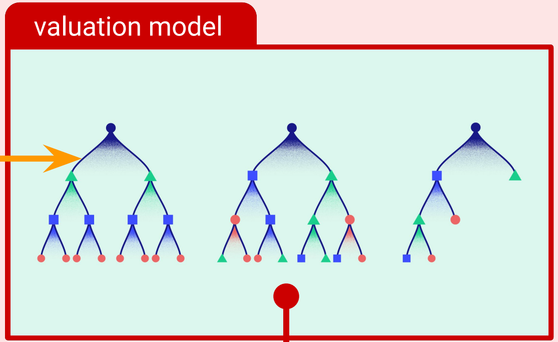
LIÈGE université

Valuation features.

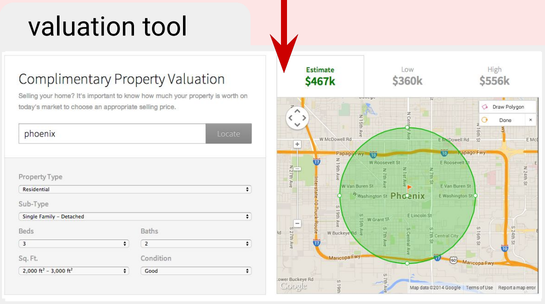
Legal real-estate data



Legal ('AI') features



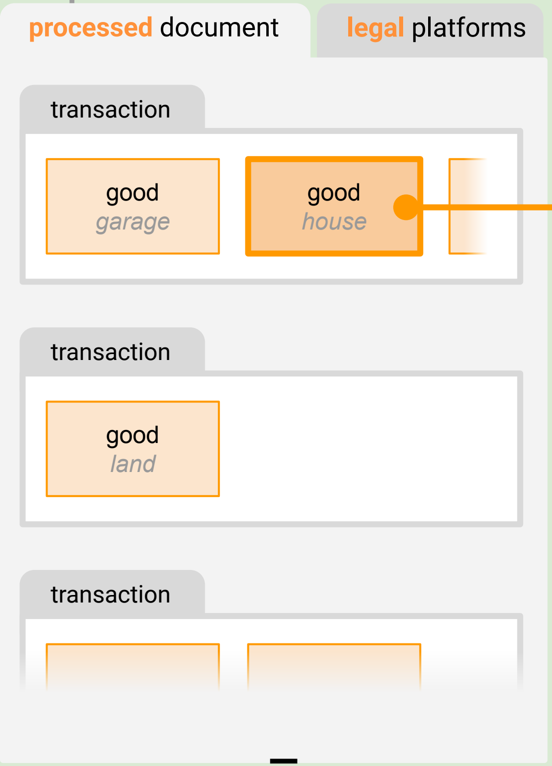
Legal features alone do not capture sufficient information to accurately predict real estate prices...



ML6 × FEDNOT

Valuation features.

Open real-estate data

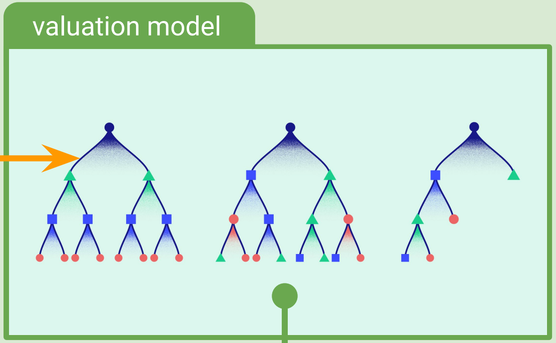


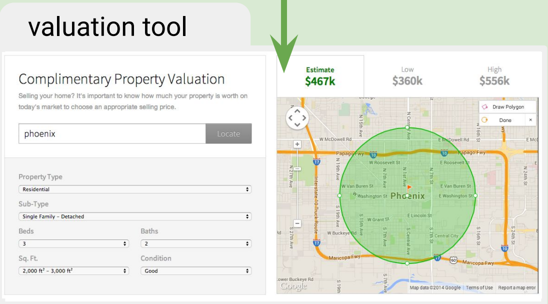
Legal ('AI') features

+

Leverage open data to expand limited feature set

- **Various types** of data sources provided by the government or community
- (Mostly) **freely accessible**
- Opportunities for **complex, more informative features**!





ML6 × FEDNOT

Valuation features.

Open real-estate data

- **Cadastral information**
  - <u>Parcel</u> area, street width, ratio, and orientation;
  - <u>Building</u> area, type (“open”, “half-open”, “closed”), facade width, and orientation

Valuation features.

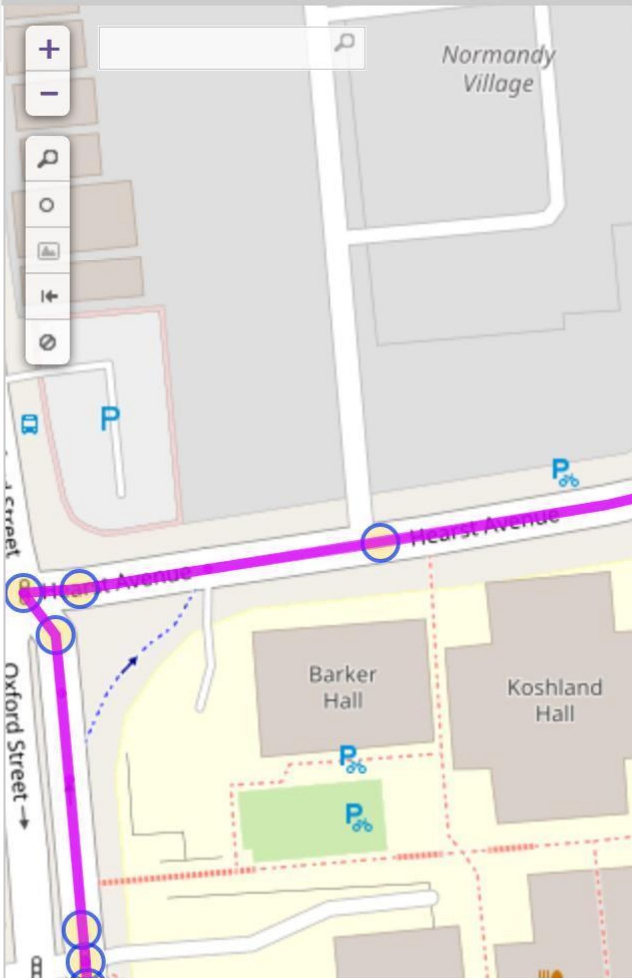
Open real-estate data

- Cadastral information
- **Height information**
  - <u>Building</u> height, volume, number of stories.

Valuation features.

Open real-estate data

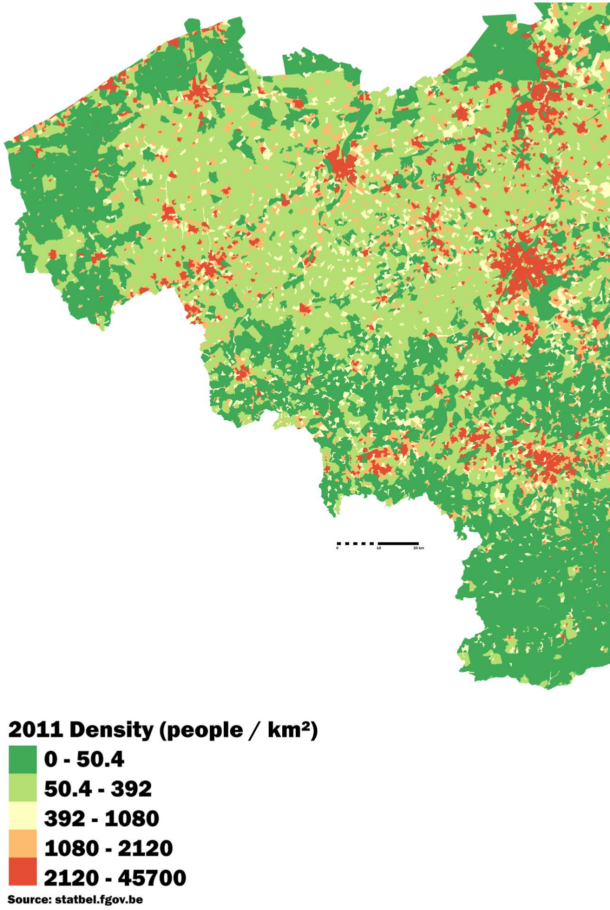
- Cadastral information
- Height information
- **Location information**
  - Distance to major cities and to nearest city center, highway (entry), primary road, railway, station, bus stop, etc.



Valuation features.

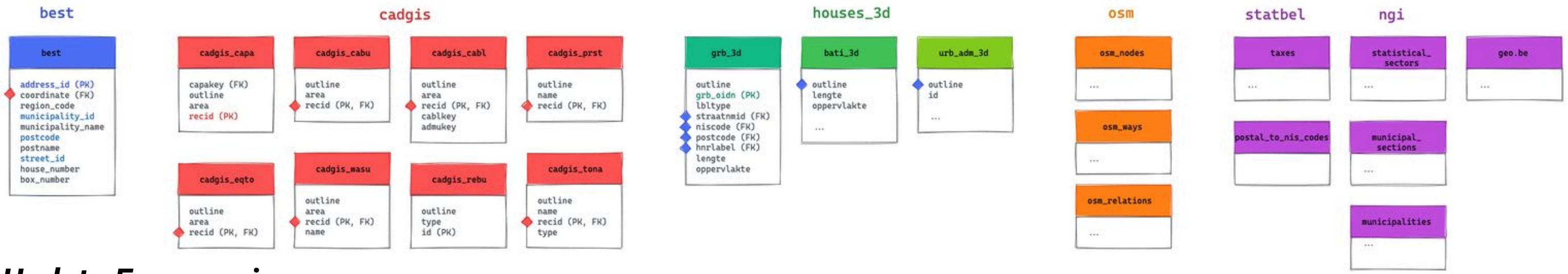
Open real-estate data

- Cadastral information
- Height information
- Location information
- **Local socio-economic and demographic statistics**
  - Municipality population size, tax percentage, prosperity index, avg. income;
  - Statistical sector cadastral income percentiles



Open Data

Sources



Update Frequencies:

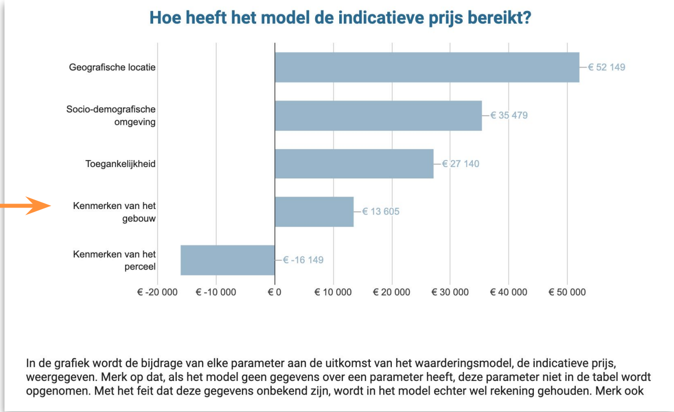
best	cadgis	houses_3d	osm	statbel	ngi
Weekly	Yearly	Wallonia - Not (2016) Flanders - Not (2016) Brussels - Yearly	Weekly	Yearly	Yearly

Valuation model.

Price prediction model

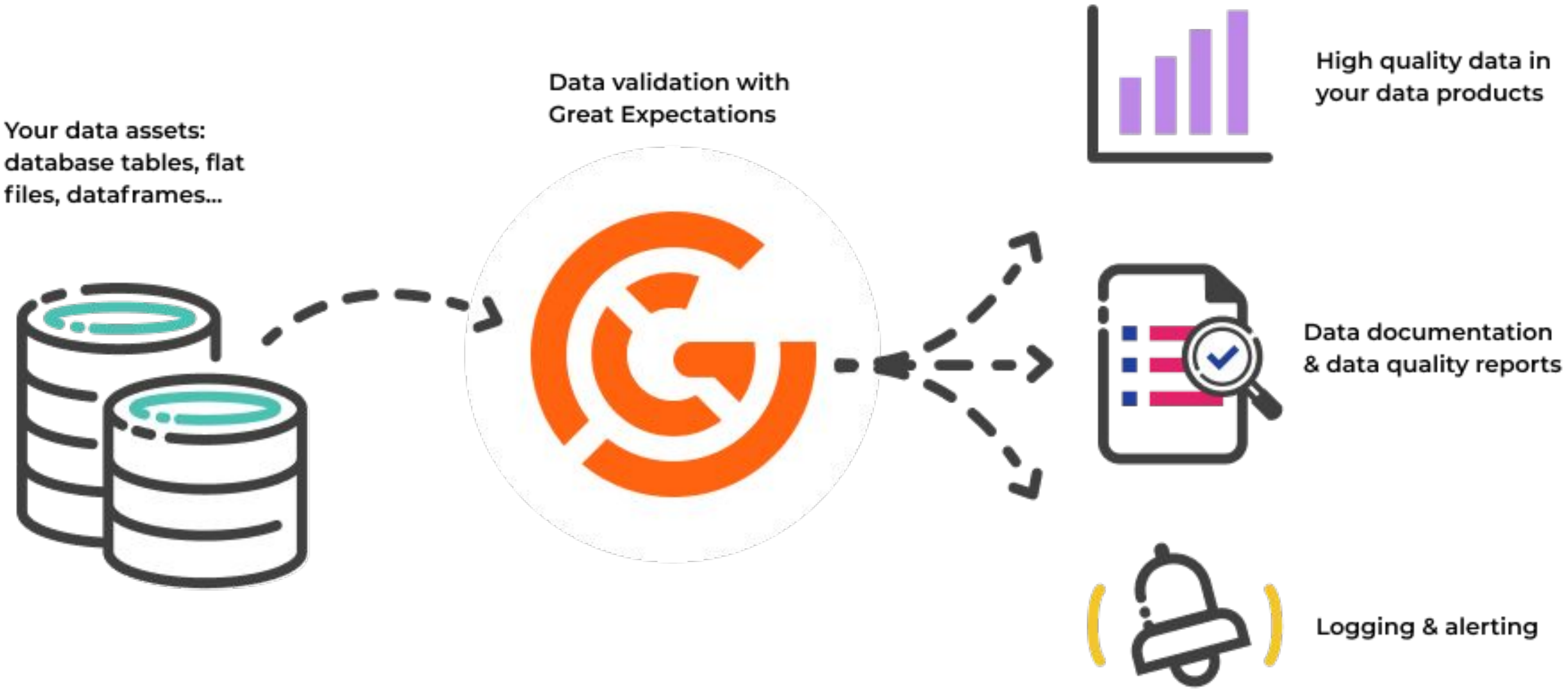
Model is not an "oracle", but supports notaries

- Important to express uncertainty.
- Shows indicative price compared to price distribution of similar properties.
- Explains how a prediction was obtained based on feature importances.



Deed data

Data validation with great expectations



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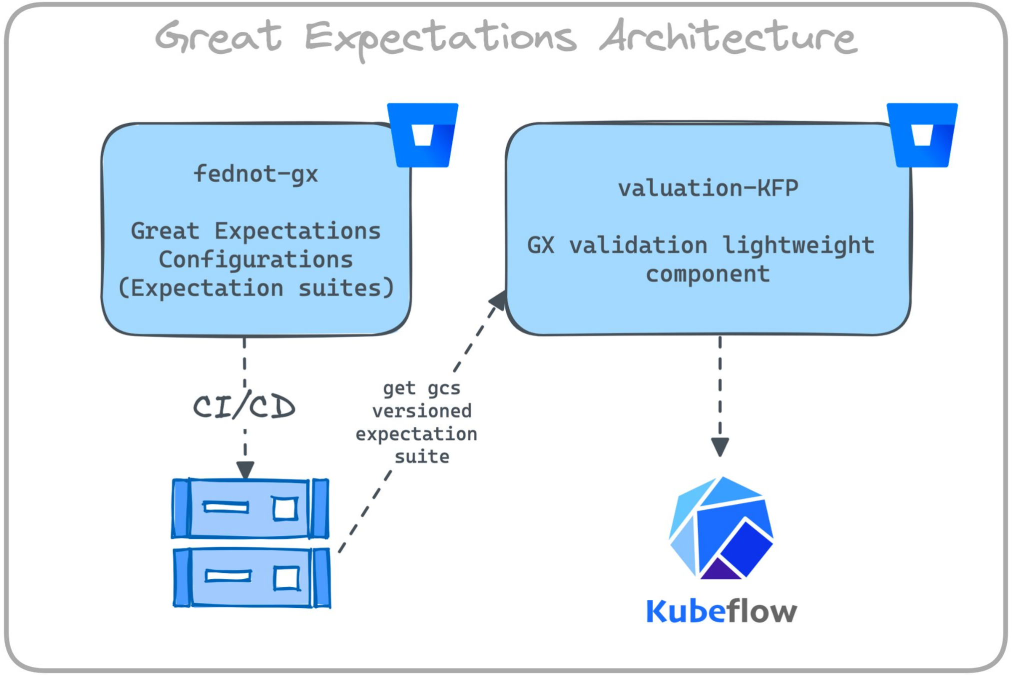
https://greatexpectations.io/

Deed data

Data validation with great expectations

- Enable non-technical people to define expectations
  - **Expectations**: A JSON file that defines rules for validation. Eg: *feature_x should be 75% not null*

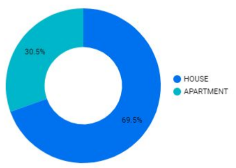
- Make the GX component reusable for multiple validation needs.



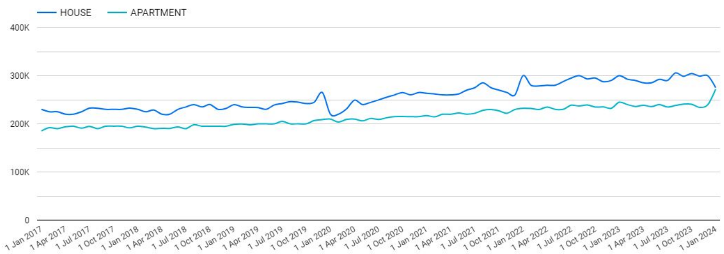
Deed data

Data quality dashboard

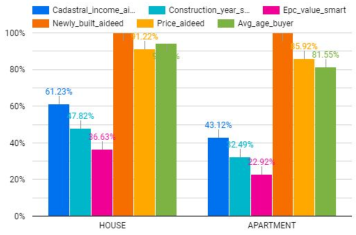
Market share



Median & Average Price



Percentage field presence

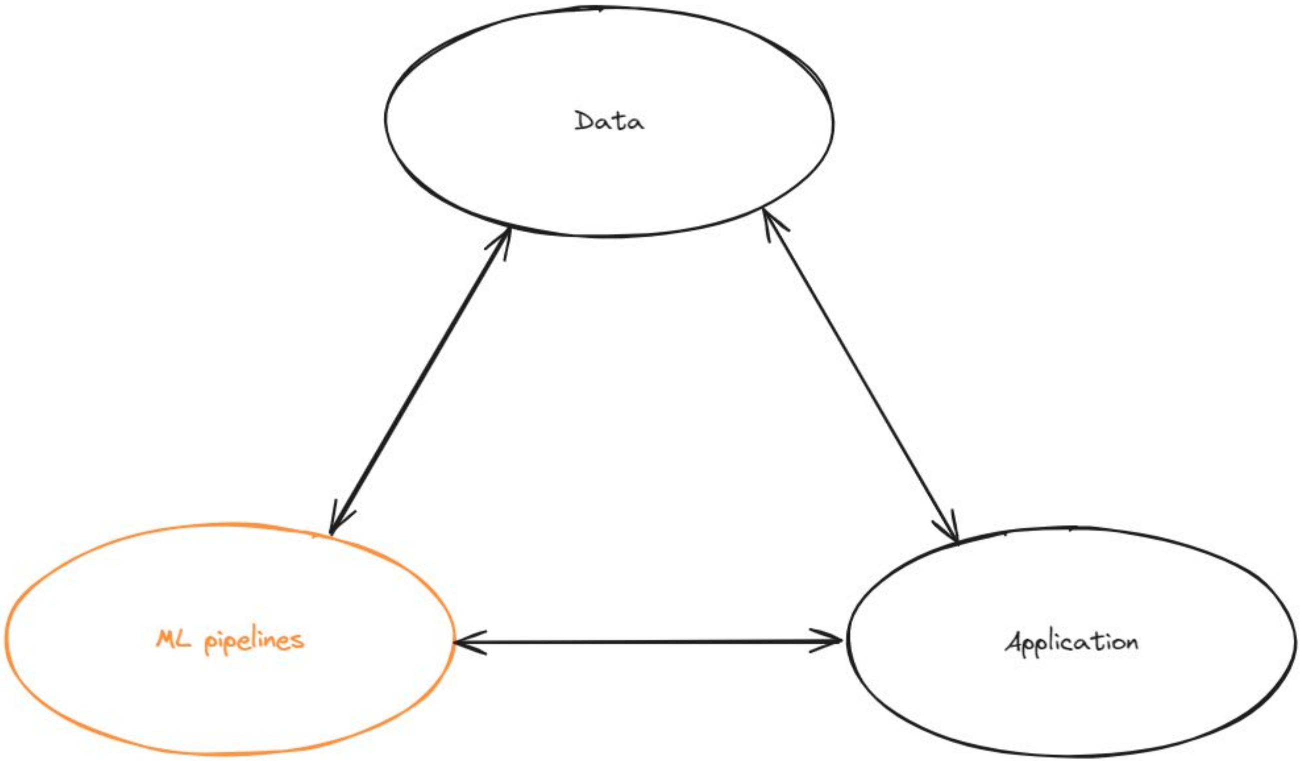


good_type / geo_level_value / Average_price / Median_price				
	HOUSE		APARTMENT	
	België		België	
Year	Average_price	Median_price	Average_price	Median_price
2017	252,705 €	229,341 €	214,948 €	192,664 €
2018	256,400 €	230,000 €	215,498 €	193,992 €
2019	268,476 €	245,000 €	224,142 €	200,000 €
2020	282,622 €	250,000 €	234,026 €	209,963 €
2021	301,602 €	268,576 €	248,156 €	222,958 €
2022	326,414 €	290,000 €	258,193 €	234,811 €
2023	328,846 €	293,463 €	262,929 €	239,296 €
2024	347,345 €	275,000 €	262,875 €	272,000 €

Median & Average Prices comparison (aideed,vgp,asf,ereg)

HOUSE

APARTMENT



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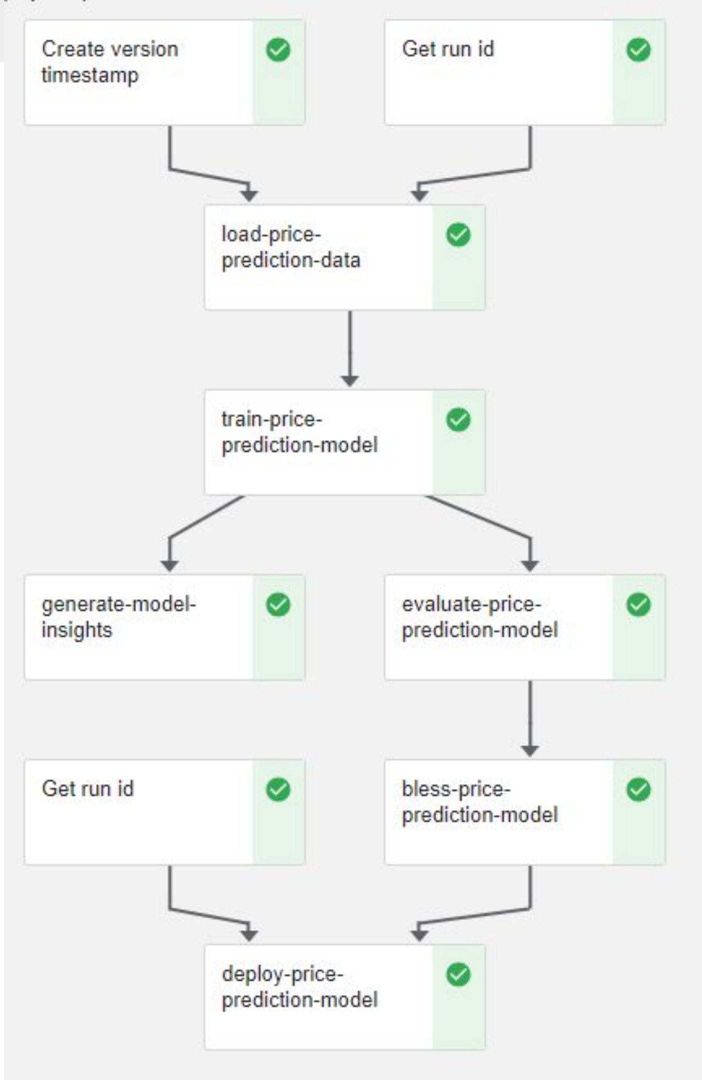
Automated pipeline to train and deploy new price prediction models

- Allows you to implement a **ML pipeline** made of different **components**, usually ran sequentially.
- Each component can be a **Docker image**
- Hosted on a **kubernetes cluster** (set of node machines for running containerized applications). Can be on the **Cloud**.
- Benefits
  - Modularized
  - Reproducible
  - Efficient
  - Scalable
  - Deployments
  - Collaboration
  - Version control and documentation

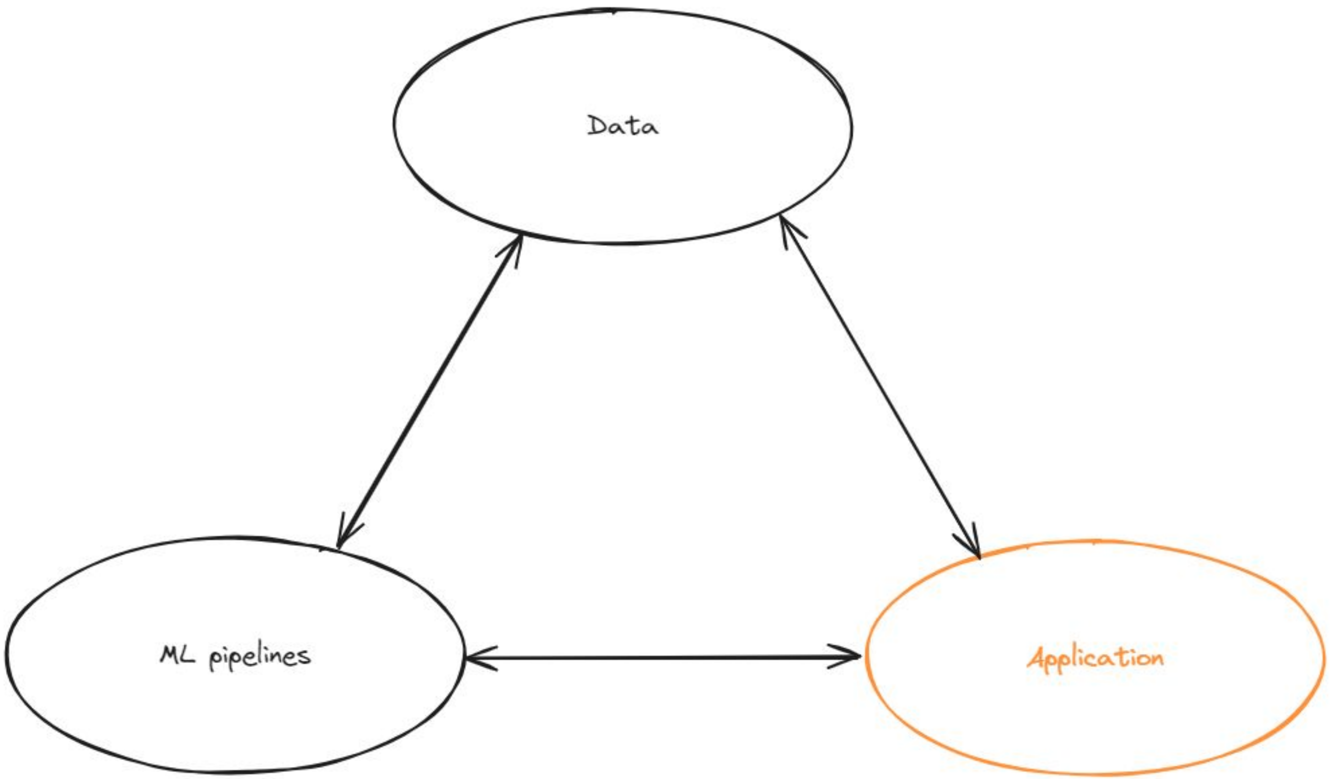


Visualisations

Explainability

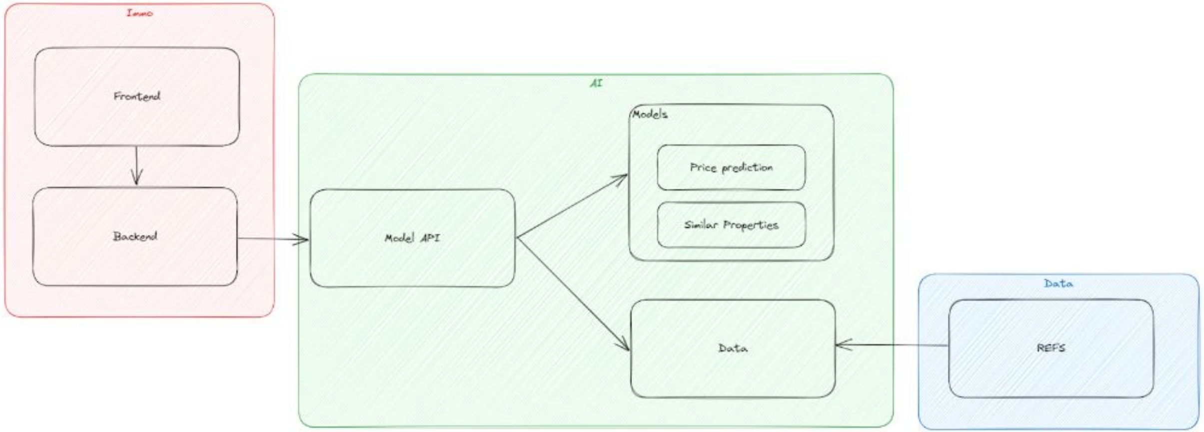
		VAN			WHT			
		nr_observations	mae	mape	nr_observations	mae	mape	nr_observ
quantile	key_features							
Q0 - Q10	0 or 1	1547	80006.176115	0.565104	870	47111.933130	0.505811	1115
	2 or 3	1312	59277.557874	0.401544	1245	37980.680478	0.409488	751
Q10 - Q25	0 or 1	1983	38821.581166	0.161699	1238	26893.919732	0.220017	1523
	2 or 3	2299	29467.034478	0.121787	1950	22944.052560	0.187566	1301
Q25 - Q50	0 or 1	3225	34544.096558	0.111164	2039	23278.130844	0.142917	2281
	2 or 3	3892	30662.822366	0.098830	3279	21559.459244	0.132382	2390
Q50 - Q75	0 or 1	3335	52391.982770	0.132128	2077	36009.678320	0.164627	2279
	2 or 3	3782	43711.812300	0.110839	3296	32903.844697	0.150859	2407
Q75 - Q90	0 or 1	1945	90583.684565	0.177171	1328	49428.070282	0.169335	1326
	2 or 3	2329	69172.979267	0.134752	1858	44220.675478	0.150880	1484
Q90 - Q100	0 or 1	1311	229875.407221	0.280143	912	116302.847821	0.245235	937
	2 or 3	1539	175906.829581	0.213262	1200	92134.481717	0.194406	937

Static HTML


Data
ML pipelines
Application

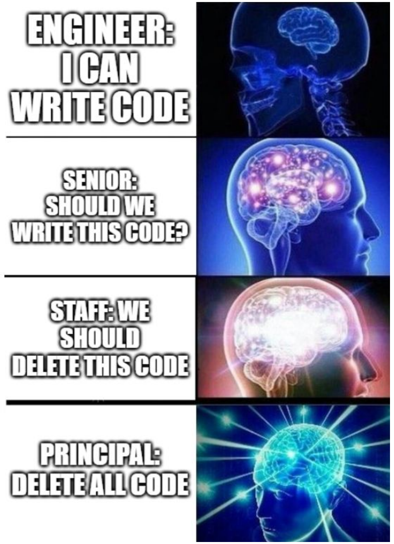
Model API

- **Cloud Run**
  - ESPv2 (API key)
  - Model services
- **GKE**
  - Hostel model
- **Bigquery**
  - Feature store
- **Storage**
  - Model artifacts



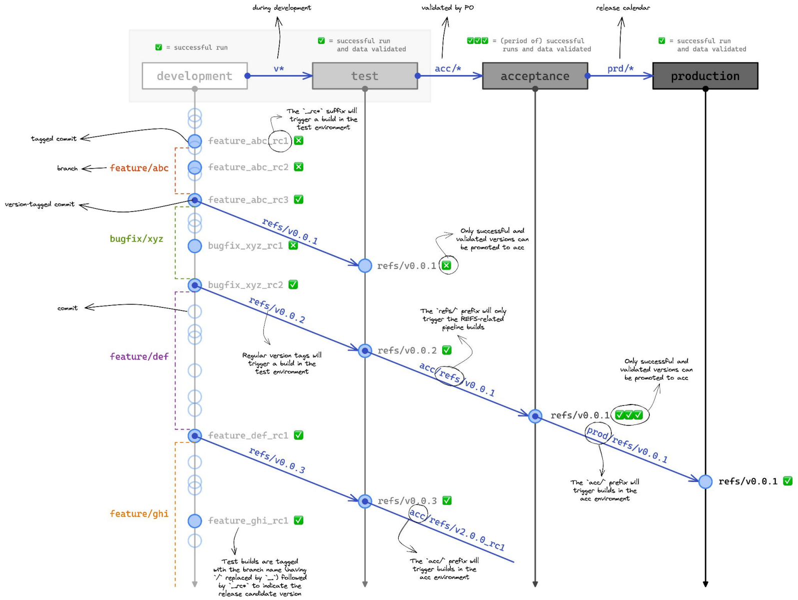
Learnings

- **“Software engineering is programming integrated over time”** - Titus Winters
  - Think enough about the time aspect
- **Documentation is not just writing stuff down**
  - Hardest part of old code is not figuring out what it IS doing, but what it is INTENDED (or SUPPOSED) to do
  - What was decided is “trivial” (you see the end result), the CONTEXT and WHY is the interesting (and hard) part
  - cfr. Chesterton’s fence
  - Keep handovers in mind → Think about your bus factor
- **Document your decisions**
  - Plan for the *future* and not for the *present*
    - Road to production should be clear
    - For example: postponing caching implementation
  - Visibility towards stakeholders!
    - “Why did *you* not do this before?” becomes “*We* decided to do other things”
- **Dare to delete stuff**



Technical Learnings

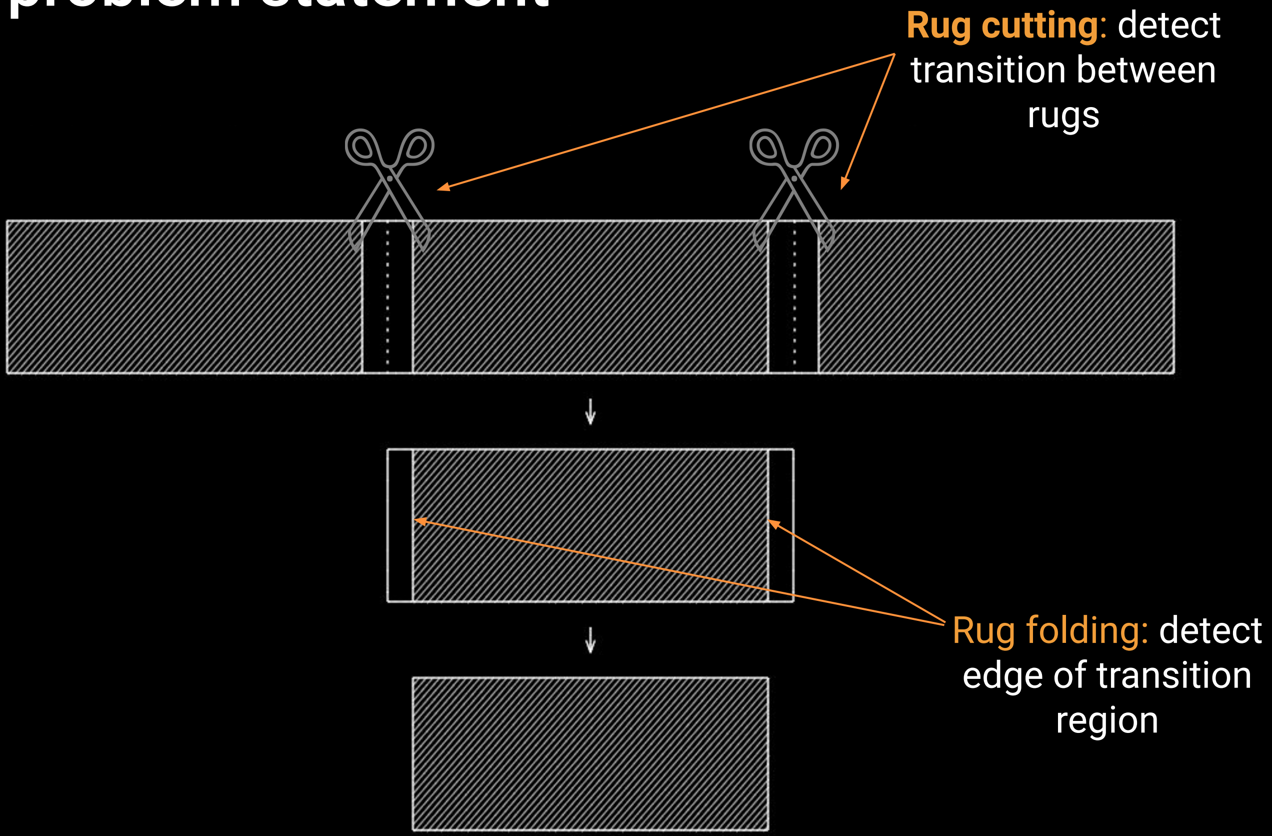
- **Build once, deploy anywhere**
  - Manual deployments to tagged deployments to ML pipelines
  - Scheduled execution
  - Balance between model performance and freshness
- **“Garbage in, garbage out”**
  - Time as a crucial feature
  - “Good” (house, apartment, cabin, …) type is hard to define
  - Notaries are too lazy/busy to provide accurate information
- **We should have started caching earlier**
  - Huge amount of deeds flowing through regularly
  - Dataflow pipelines took a loooong time and regularly went OOM



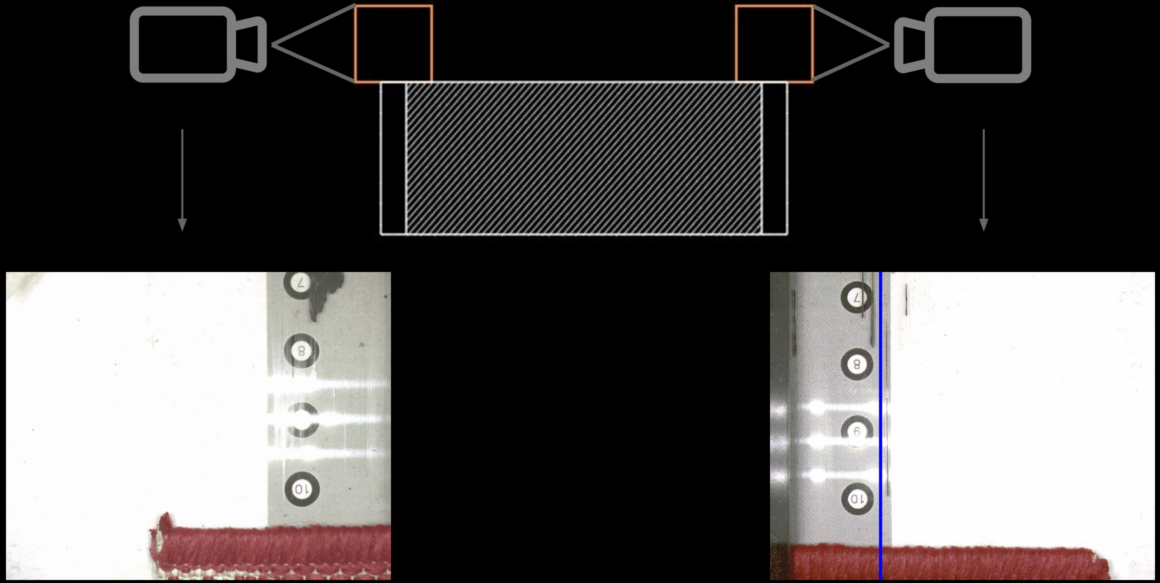
Use case deep dives

Rug cutting detection

Context & problem statement



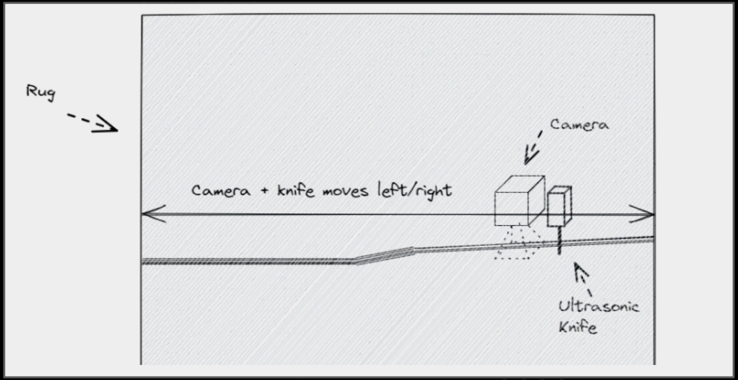
Rug folding

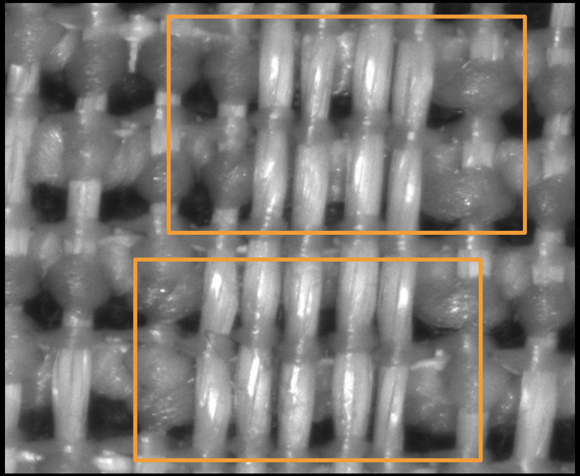


Rug cutting: 2 AI models

- Line Search: The rug must be stopped when the outer edge of the cutting line is in view of the camera. An approximate distance of where to stop is known, but a visual check based on image processing is necessary for accurate localization.

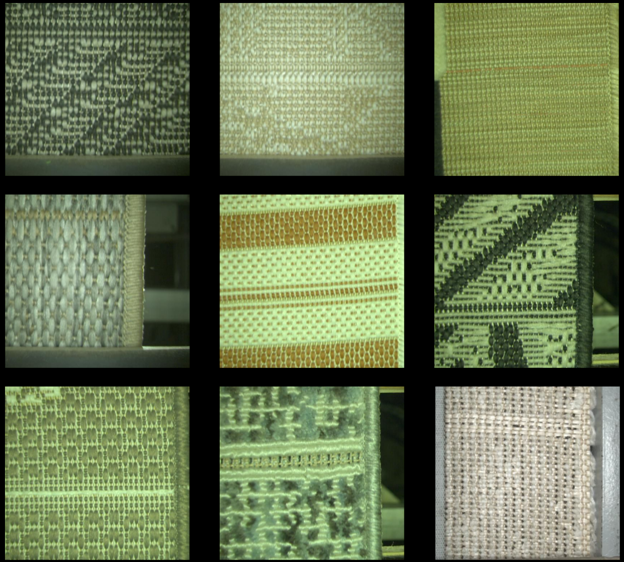
- Line Tracking: Once the outer edge of the cutting line is found and centered, A camera and an ultrasonic knife move along the width of the rug while adjusting the rug position based on the images to make sure that a cut is made at the correct position.





Rug cutting: different carpet types

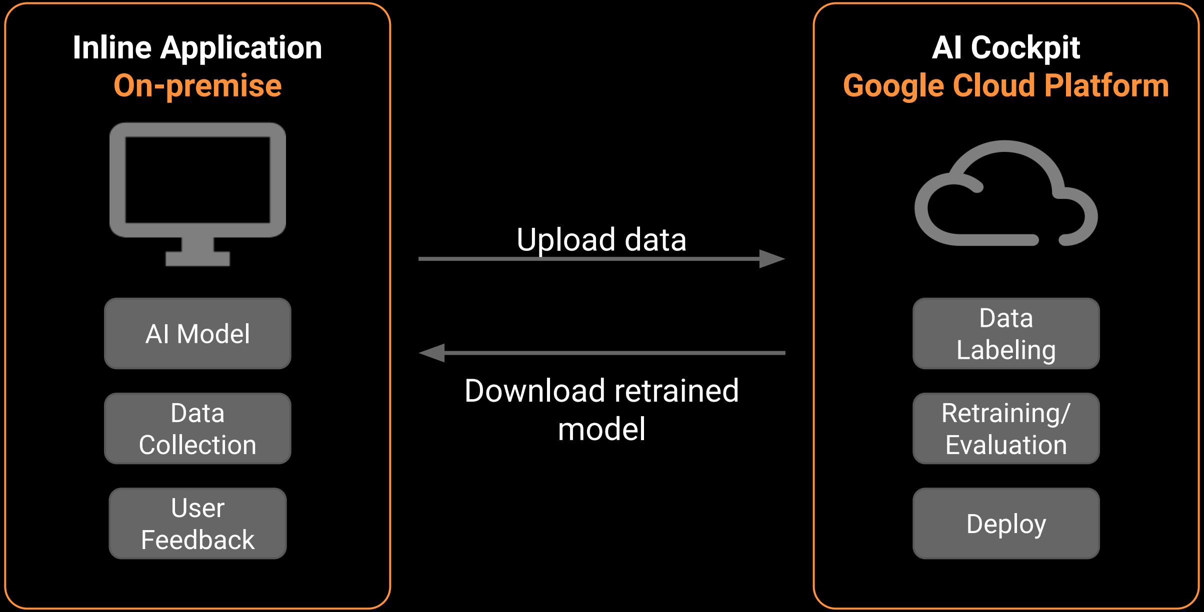
S1 carpets



L1 carpets

Solution helicopter view

~~Hybrid AI~~,
~~Hybrid solution~~
Hybrid architecture



The integration study has produced three key decisions

Compute Device

Camera Type

PLC-centric vs PC-centric

Traditional Windows Desktop

+ Remotely maintainable by IT
+ Known environment

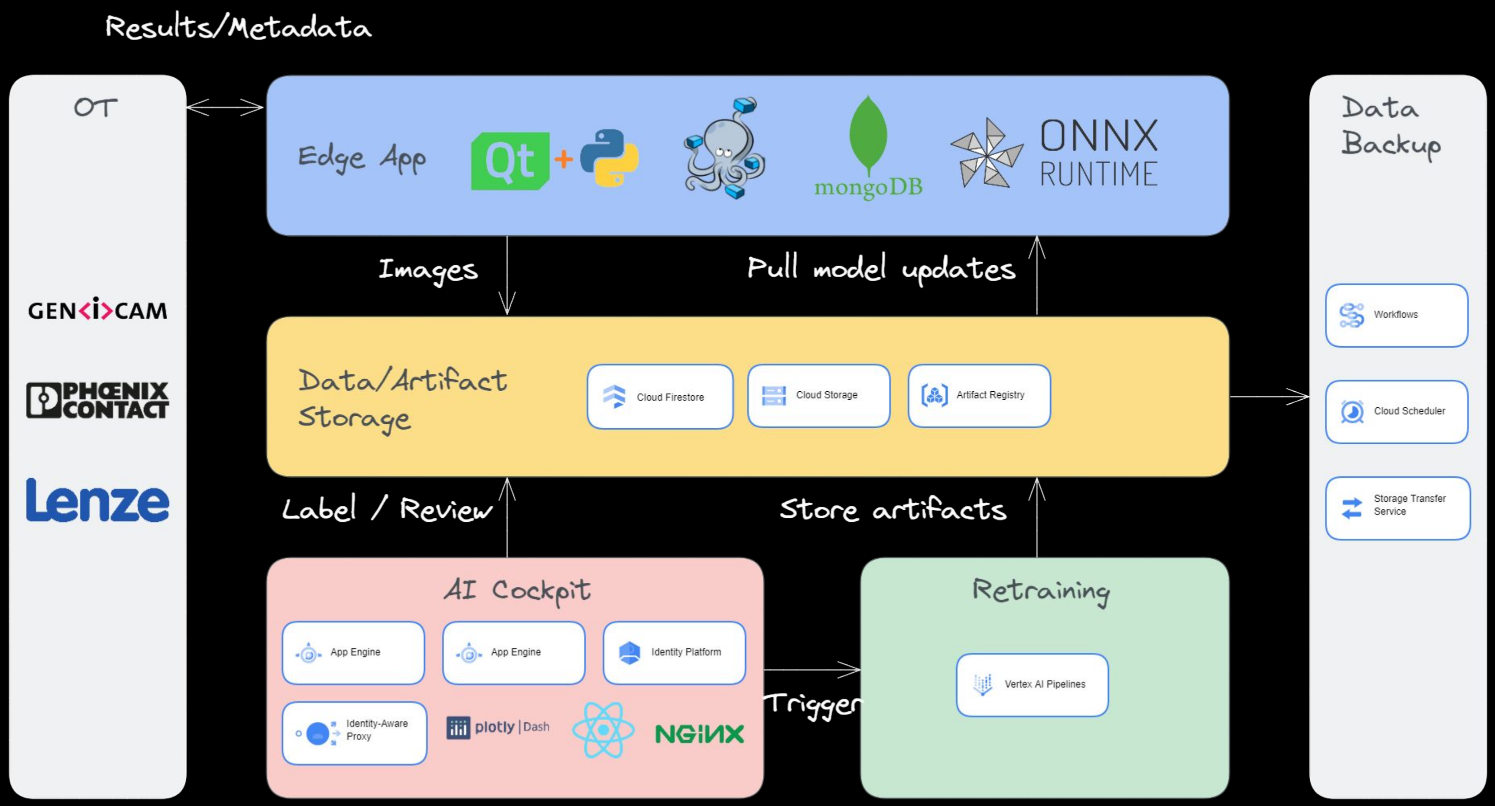
- Windows OS not suited for real-time industrial applications
- Increases development difficulty
- Long lead times for purchase

Nvidia Jetson

+ Industrial single-board Linux computer with GPU
+ Small form factor (DIN rail mount)
+ Faster availability (+/- 1 month)
+ Enables standardization to speed up more followup use-cases

- Learning curve because of Linux OS

High level architecture and tooling.



Use case deep dives

Data Driven Sales

Randstad

Sales effectiveness tool

WHAT WE DID

We developed a scalable AI solution that allows their sales consultants to focus their time on **contacting companies who have real potential** for Randstad, and enabling them to build conversations based on accurate and relevant information

Thus increasing sales effectiveness by sending consultants to the **right company** at the **right time**, driven by the **right information**

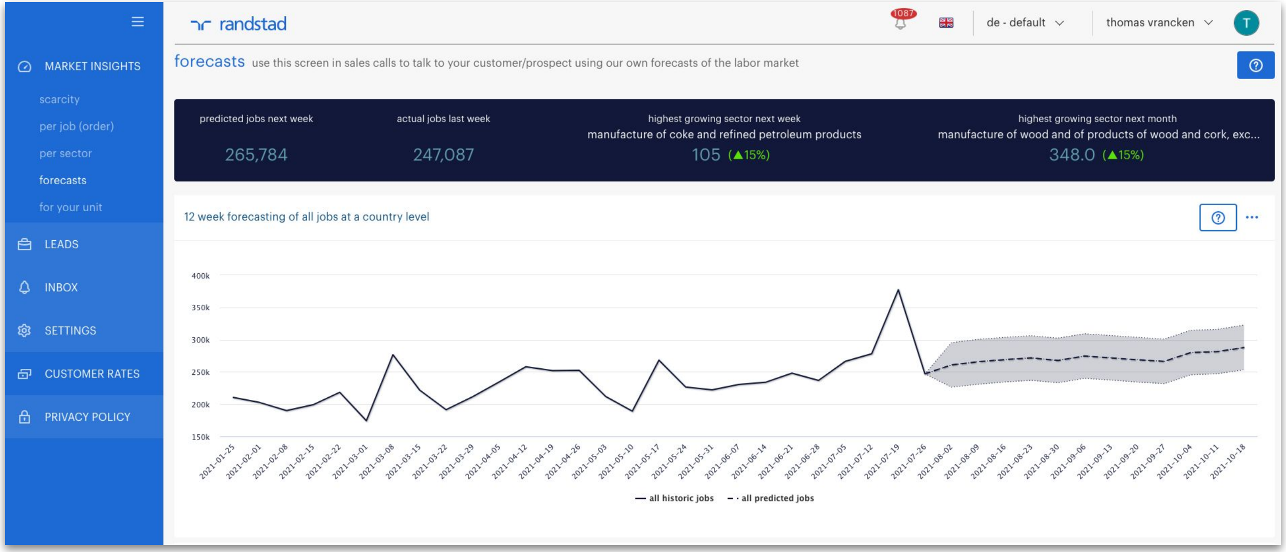
The tool is currently actively used by around 10.000 sales consultants spread over 6 countries

> “Our sales consultants were spending only 25% of their time on the right clients. With the AI enabled “sales effectiveness tool” that hit rate has gone up to 70%
>
> Gunther Ghijsels,
> Chief Digital and Information Officer at Randstad Group

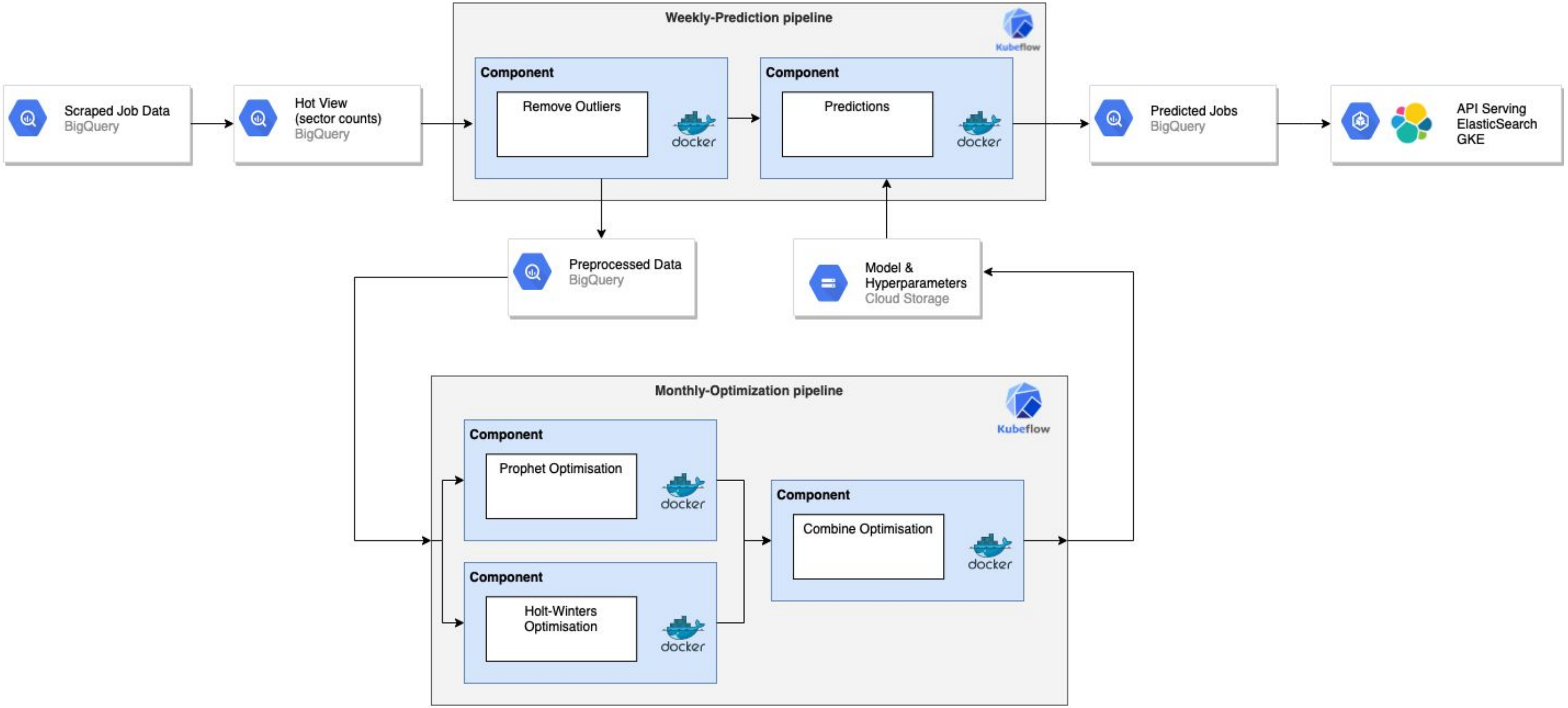
randstad

Demand forecasting track

- Business use case:
  *"Predict the amount of **Job Offers** Randstad will receive in the next **12 weeks** for a certain **Industry** in a certain **country**"*



Demand forecasting pipeline



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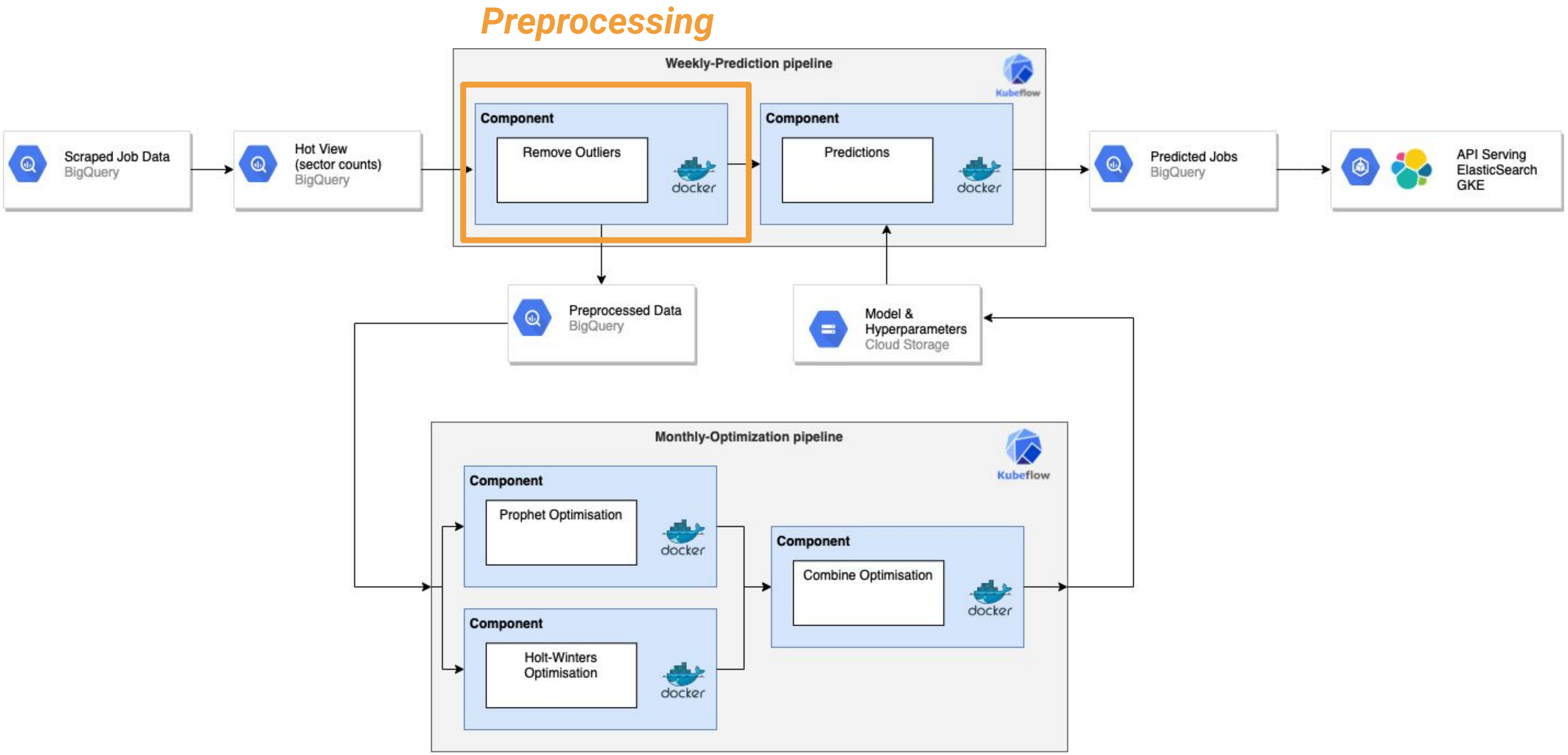
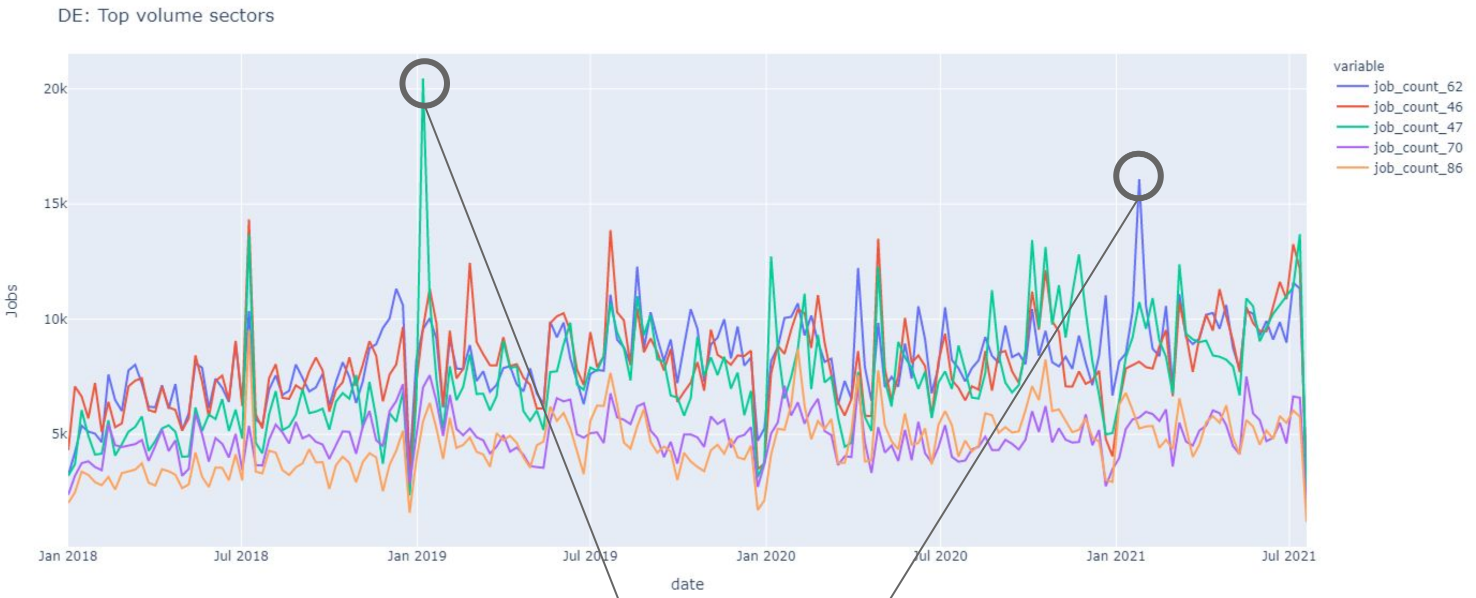
Demand forecasting pipeline



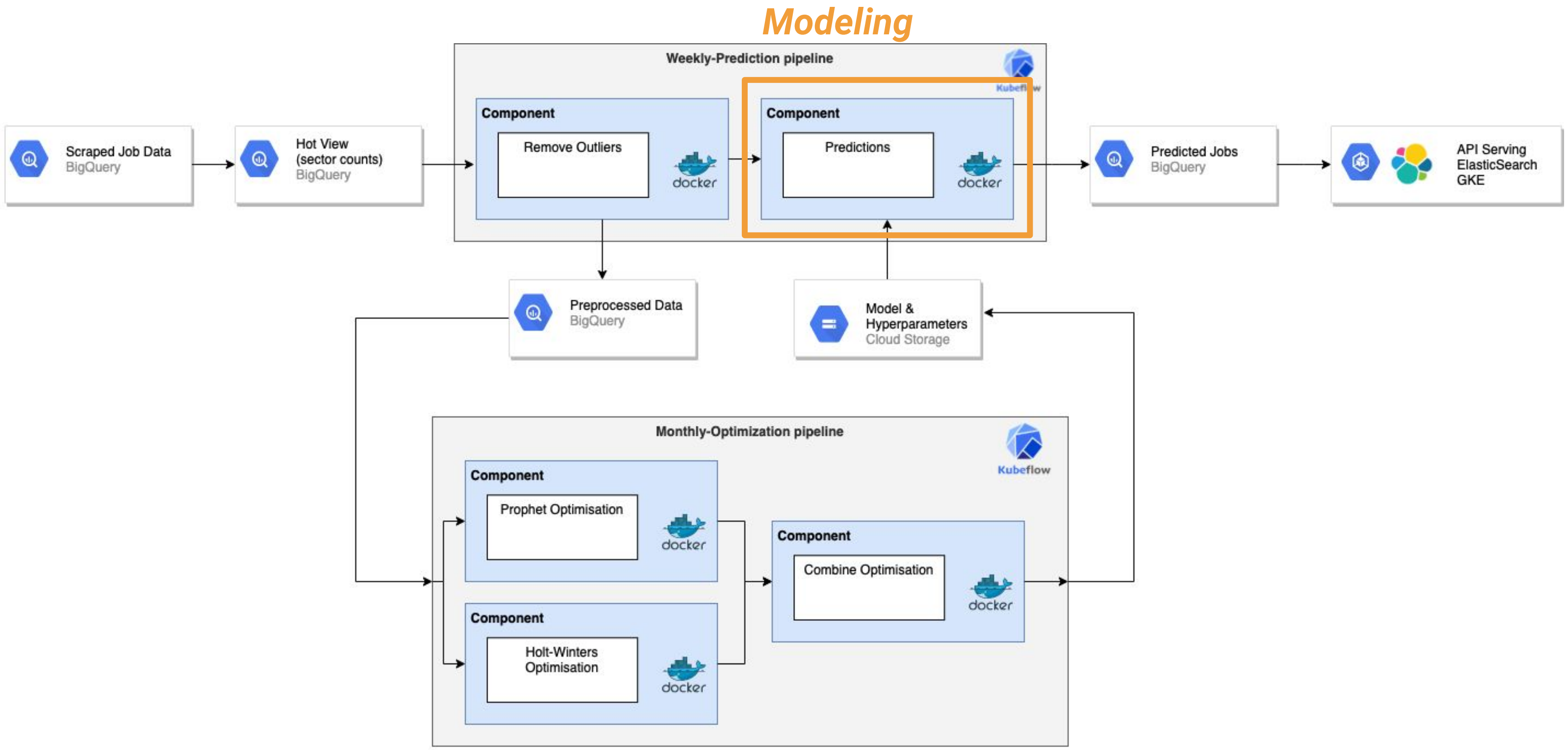
Preprocessing.

Outlier Detection



Perform outlier-detection.

Demand forecasting pipeline



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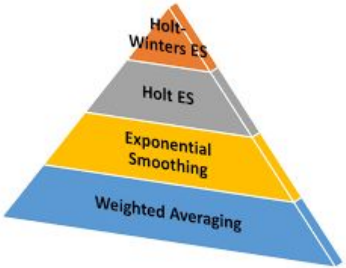
Models

V1 Phase - Endogeneous

Prophet

PROPHET

Holt-Winters



Other implementations tested:

- *(S)ARIMA(X)*
- *LSTMs*
- *XGBoost*
- *External data:*
  - *Corona data (public dataset in BQ)*
  - *Oxford Economics indicators*

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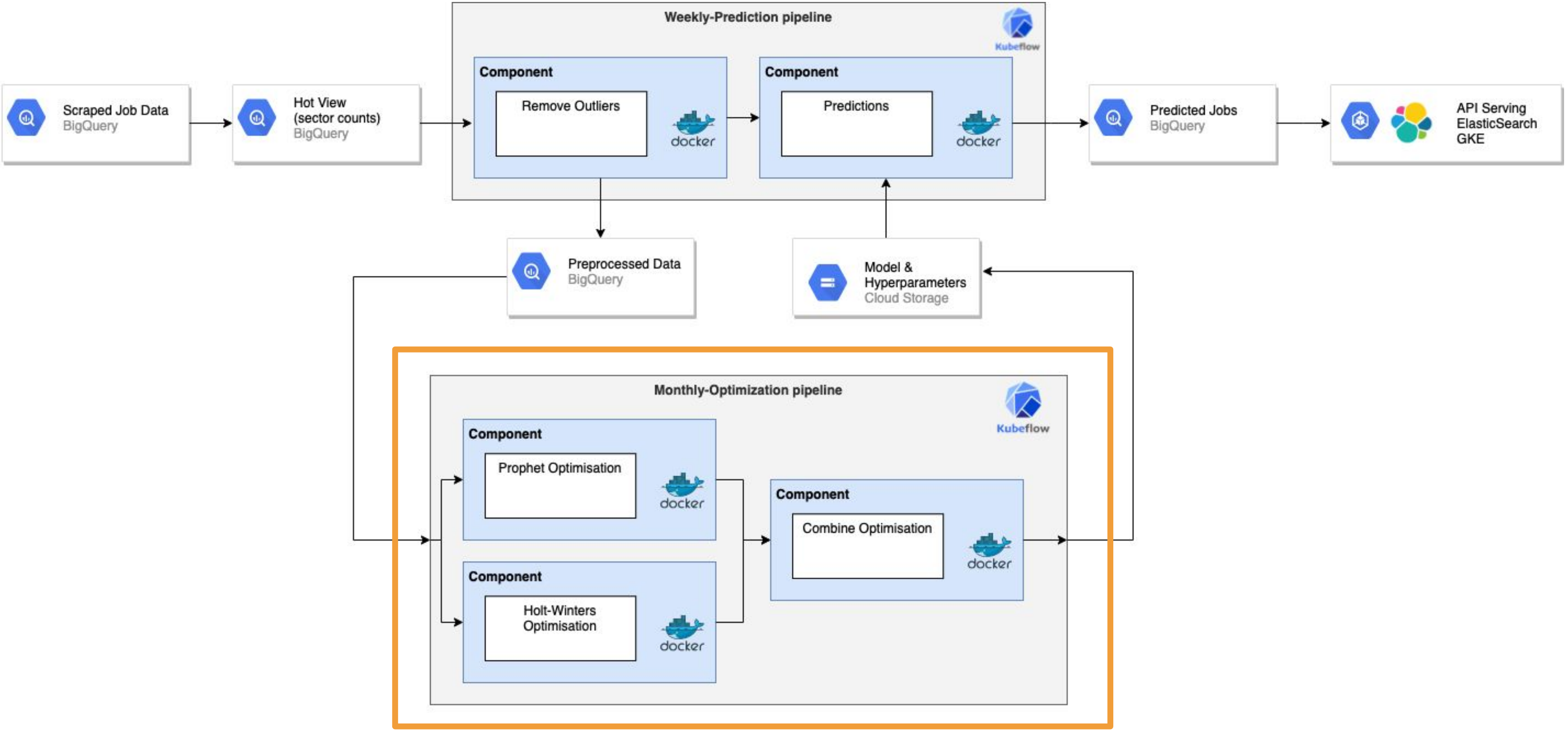
Optimisation.



Optimisation & Performance

Optimisation Design

Hyperparameter optimisation

- Different sectors in different countries behave very differently (trend, seasonality)
- Frequently and automatically adapt models to data shifts
- Specs:
    - *Grid Search*
    - *Cross Validation* (10 folds, country specific)

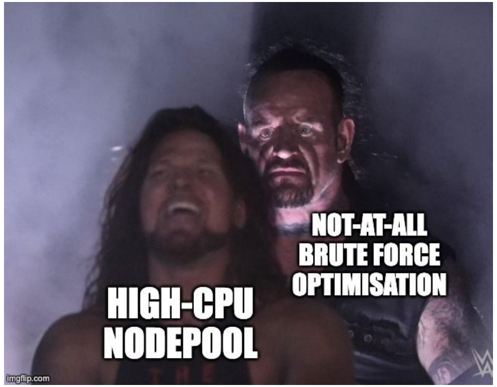
HP grid for Prophet

```
{
    'growth': ['logistic', 'flat', 'linear'],
    'seasonality_mode': ['multiplicative', 'additive'],
    'changepoint_prior_scale': [0.001, 0.05, 0.5],
    'holidays_prior_scale': [0.1],
    'n_changepoints': [1, 5, 40],
    'weekly_seasonality': [True],
    'yearly_seasonality': [True, False],
    'daily_seasonality': [True],
    'uncertainty_samples': [False],
},
```

ML systems design

Kubeflow Pipeline

- Allows you to implement a **ML pipeline** made of different *components*, usually ran sequentially.
- In this case, we used **high-CPU nodepool** to run heavy job-loads much more efficiently
    - “Brute forcing” the optimisation



ML systems design

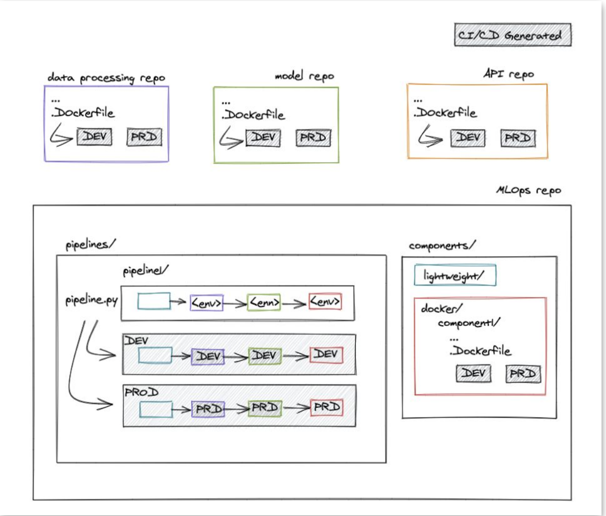
CICD

GitLab GitHub Bitbucket

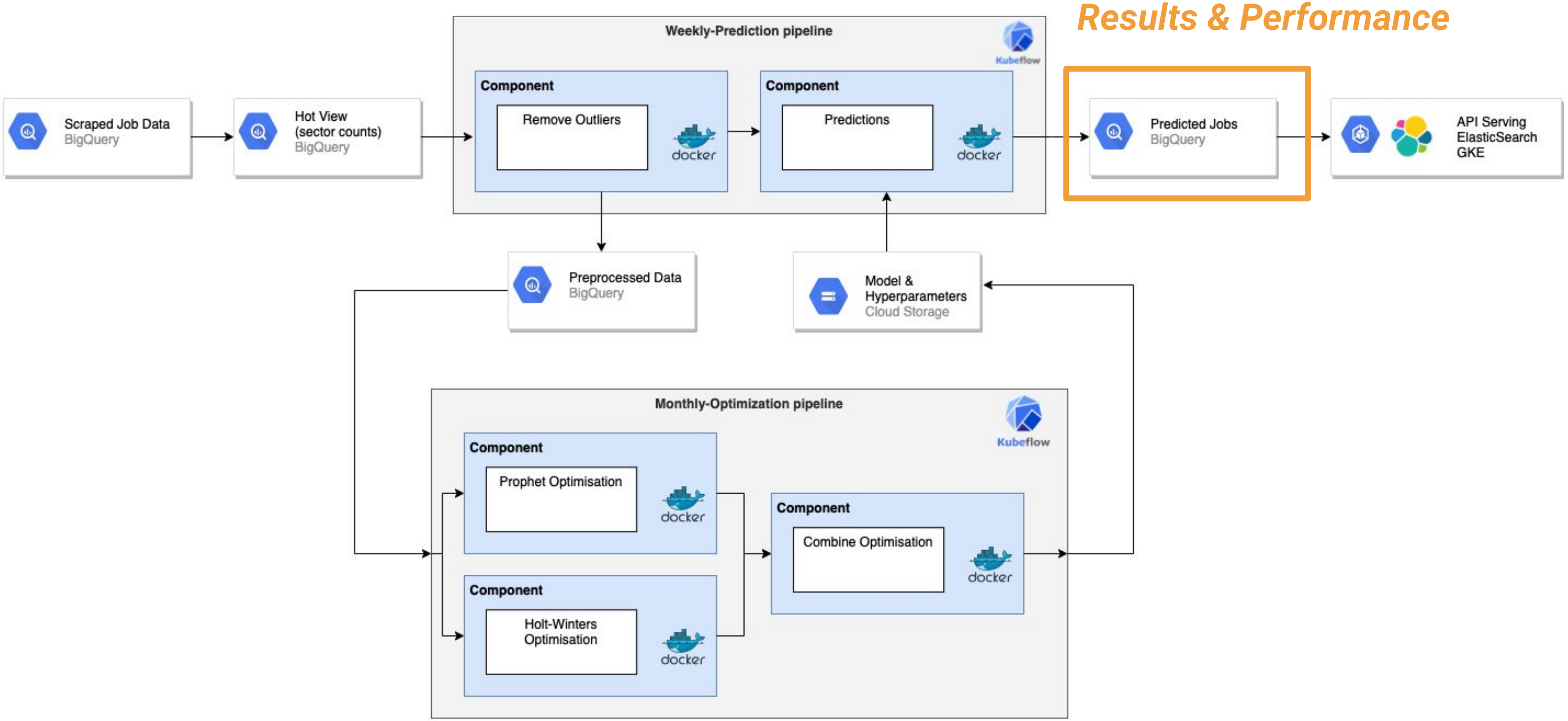
Continuous Integration and Continuous Delivery (CICD)

To deploy and run everything for

- Change in codes
- New country
- Multiple environments (sbx, dev, prd)



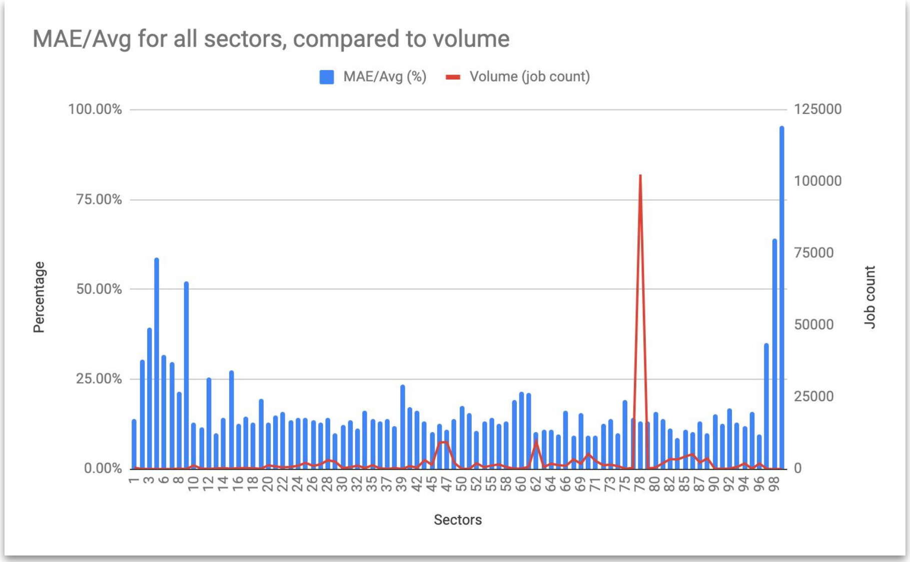
Results & Performance



Performance & monitoring

Challenging to track

	avg_vol	mae	rmse	mape	mae/avg
Average	2516.397727	316.0888188	389.3687453	16.56189739	0.1754183255
Std Dev	10953.91528	1454.313019	1781.531703	9.801958588	0.1295814985



Monitoring dashboard: You can compare historical predictions of live system to actual values

- **Human understandable metric**:
  - Mean Absolute Error/Average volume


ML APPLICATIONS
ML APPLICATIONS EVERYWHERE
imgflip.com


ML APPLICATIONS
WE SEE
ML BEING APPLIED
TO EVERY INDUSTRY
imgflip.com

A few (other) example of ML applications.

Document AI

Pricing

Video games

Quality control

Robotic

Customer clustering

Customer support

…

… 300 ML use cases: https://www.evidentlyai.com/ml-system-design

Project phases & challenges

Build different stages of your solution

Proof of Concept

Use easily available data to show that your model or solution can work.
Low efforts.
Prove the feasibility and value.
Iterate fast.

Minimum Viable Product

Just enough features for a small set of users to start using it.
Gather feedback and make sure that it is designed in an optimal way.

Productionisation / scaling

Build the infrastructure to finally deploy your solution and let users use it.
Gradual roll-out to more and more users in more and more markets.
Deploy better models, attract more users, go to new markets, maintain the solution, …

Maintenance

Keep the solution up and running.
Monitor resources and performance.
Update packages and dependencies (software around solution change).
Security and up-time.

POC	MVP	Productionisation / scaling	Maintenance	…
2 weeks	*2 months*	*6 months*	*As long as it's up…*	

Time needed for each part of the project

Analysis	POC	ntenance	…
2 weeks	*2 weeks*	*s it's up…*	

Functional Analysis

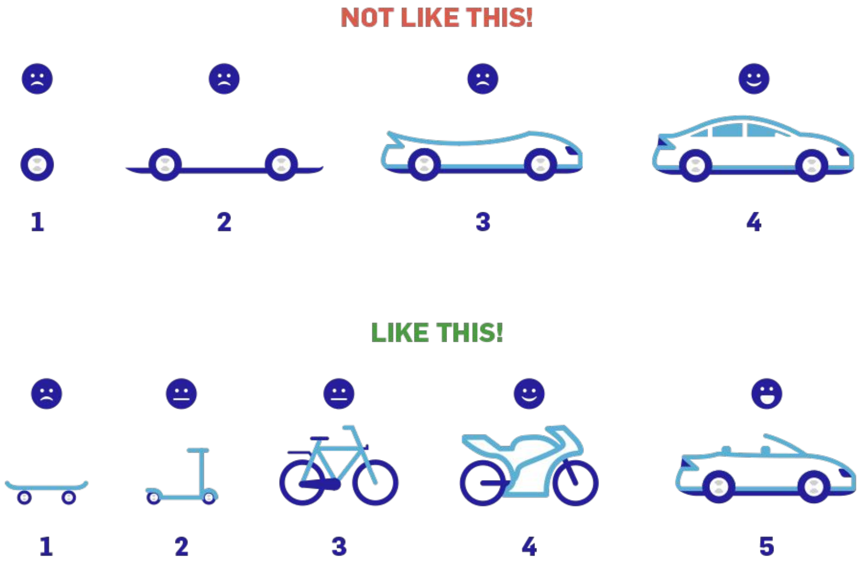
Discussion, intervie
and workshops with
stakeholders and us
to fully understand t
context of the syste
what problem it will
solve and what value
will bring.
Includes defining an
designing the soluti

Maintenance

ep the solution up and
nning.
nitor resources and
formance.
date packages and
endencies (software
und solution change).
urity and up-time.

At each stage, your product should be usable

Building a Minimal Viable Product



Data science projects are challenging to bring to production

Breaking the myth

*“**87%** of data science projects never make it into production…”*

Forbes

VentureBeat

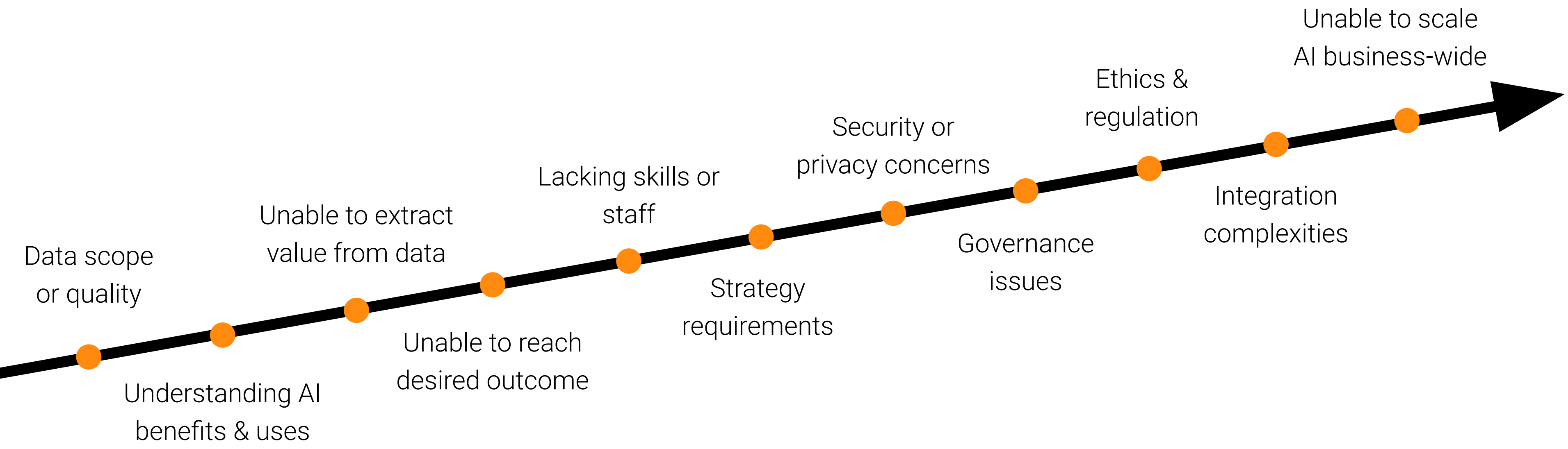
https://mtszkw.medium.com/why-do-87-of-data-science-projects-fail-and-are-we-sure-that-it-is-true-fe8b5ba1404c

(Might not be a factual number…)

But data science project are still challenging to actually roll-out to the real world.

AI Journey Challenges.

While AI is an enabler for strategic priorities, it doesn't come without its challenges.



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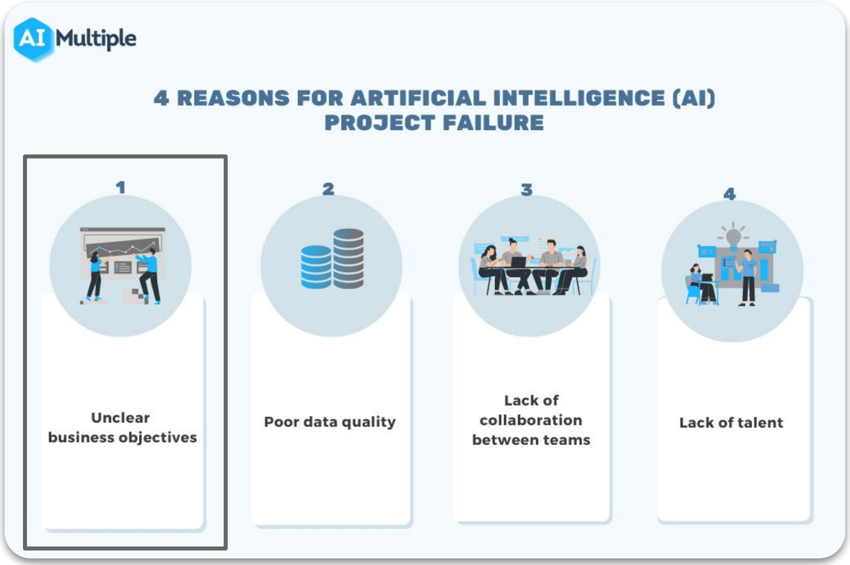
Let’s look at reasons for project failures



How can we prevent this from happening?

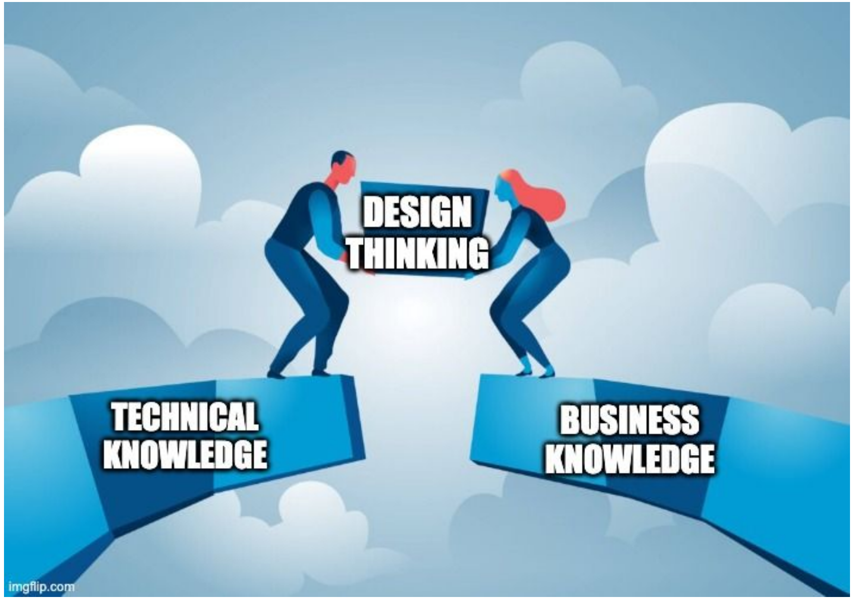
https://research.aimultiple.com/ai-fail/

Project definition framework

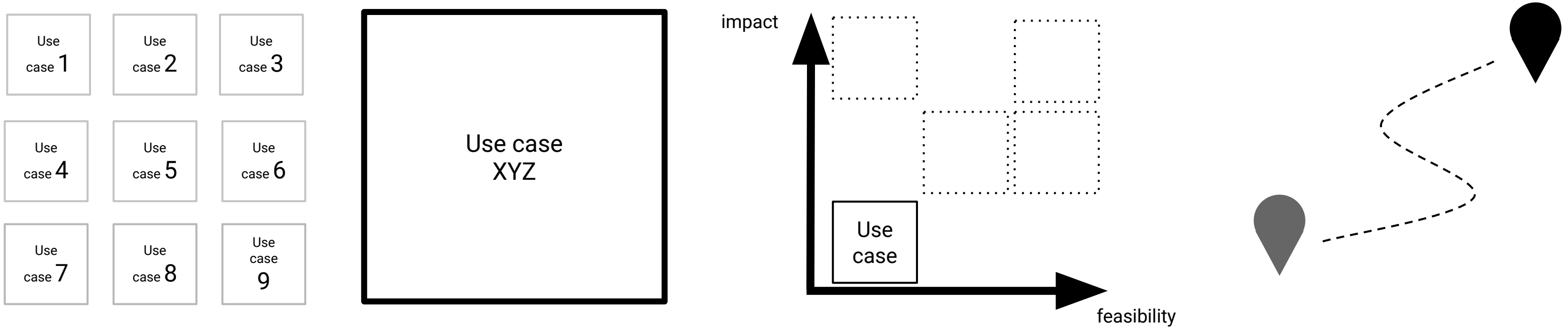
Process to define new use cases.

How to get started?

- **New ideas** do not come spontaneously
- Proactively organise **workshops** to identify how ML can create value in an organisation.
- Use **design thinking** techniques.
- Make sure to have the **right people around the table** (decision makers, stakeholders, users and (ofc) engineers).
- Spend enough time in it - **starting in the right direction** is key.



Framework to define an AI use case.



1 Identify AI opportunities

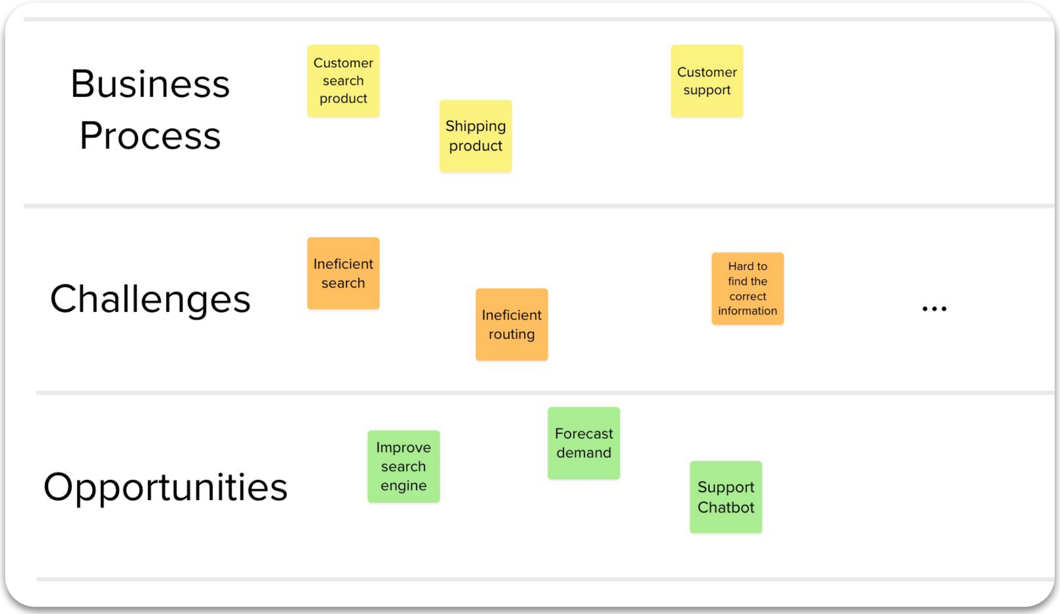
2 Evaluate and refine selected use cases and their feasibility

3 Prioritize top use cases to kickstart AI

4 Define the roadmap towards this AI use case

Identify opportunities

- Ideate and map user process
  - Identification of **business opportunities**
  - Identification of **challenges**
  - **Opportunities**: where can AI help?
- Cluster opportunities
- Name AI use cases



Use case template.

- How to quickly iterate over a few use cases?
- How to efficiently capture the point of view of different people?
- How to set the vision on a specific use case?

<table>
<tr><td colspan="2">Use Case: [Cool Name]</td></tr>
<tr><td rowspan="2">What?

[Describe the use case in 2 sentences]</td><td>Value
[Score out 5 - flash vote]
☆ ☆ ☆ ☆ ☆</td></tr>
<tr><td>Feasibility
[Score out 5 - flash vote]
☆ ☆ ☆ ☆ ☆</td></tr>
<tr><td colspan="2">Why?
[Purpose of the solution - e.g. reducing costs, helping users, climate, …]</td></tr>
<tr><td colspan="2">Who?
[Stakeholders benefiting from the solution (e.g. customers, users, role X, …)</td></tr>
<tr><td colspan="2">How?
[Approach, simplified]</td></tr>
<tr><td colspan="2">Challenges?
• …
• …
• …</td></tr>
<tr><td colspan="2">Evaluation?
[Metrics and success criteria]</td></tr>
</table>

Prioritisation matrix.

How to evaluate the different use cases?

Business Value

Major projects/Big wins
The results are often not easy to realise but they can have a big impact on the organisation.

Quick wins
These use cases have the most potential to delivery successfully and are typically delivered first to create momentum.

Thankless Tasks
These use cases are typically not the use cases that you should leverage and deliver.

Fill-ins
These use cases are “nice to have” as they are easily to deliver but have a lower business impact.

Technical Feasibility

Define and scope your project.

Which questions to answer before getting started with the selected project? (Often done offline, after the workshop)

Define value drivers

Set success criteria

Identify challenges

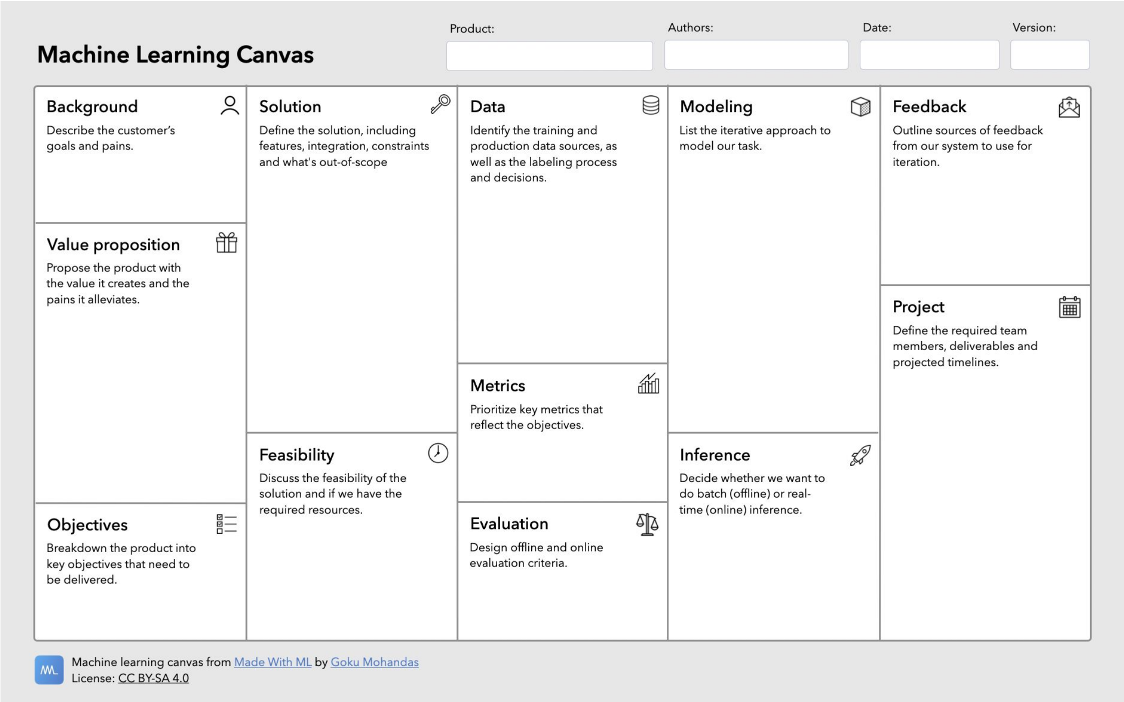
Think about intermediate milestones that show value

Define building blocks

Estimate time & budget

Define and scope your project.

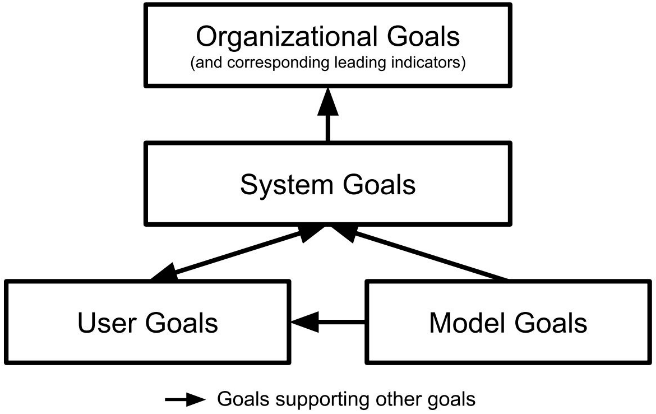
Product design template



https://madewithml.com/courses/mlops/product-design/

Aligning your solution with goals on different levels.

- **Organizational goals**: Innate/overall goals of the organization.
- **System goals**: Goals of the software system/feature to be built.
- **User goals**: How well the system is serving its users, from the user's perspective.
- **Model goals**: Quality of the model used in a system, such as performance.



These goals should be aligned with each other

Other concept: Design thinking

Same ideas, different framework (coming from front-end engineering)

6. Implement

Once the design is finalized, begin the development process using appropriate technologies and frameworks.

1. Empathize

Engage in qualitative research methods such as interviews and workshops to deeply understand the users, their needs, and their pain points.

4. Prototype

Build a **mock** application to validate whether it fits your users needs.

2. Define

Clearly articulate the user's needs and challenges based on the insights gathered during the empathize phase. Map out the user's interaction with the solution.

3. Ideate

Engage in collaborative sessions to generate a wide range of solutions and ideas.

5. Test

Monitor user interactions and gather data to measure the application's success. Maintain an ongoing feedback loop with users to continually refine and improve the application.

User adoption

Typical challenge in software development. Often challenging with ML applications.

“You can have the best model with the best data, success is always dependent on how users will adopt it.”

Ways to ensure user adoptions:

- **Power users**: Work with users since day 1. Throughout the use case ideation and during development. You receive critical feedback and can get champions who fully understand the solution to spread its usage once developed.
- **Change management strategy**: From executives and process experts.
- **Integration**: Make sure if works with users favorite tools (a new board in existing platform has much higher chances of being utilised than a new program/website).
- **Documentation**: Clear explanation of *how the model works, performs* and *should be used*. Training program, videos, tutorials, FAQs, support line, …
- **Monitor usage**: … and improve the solution from it.

When not to use Machine Learning?

It's not always the right solution...

- Clear specifications are available
- Simple heuristics are good enough
- Cost of building and maintaining the ML system outweighs its benefits
- Correctness is of utmost importance
- ML is used only for the hype (e.g., to attract funding)

Examples of these?

(Really) accurate predictions might not even be <u>that</u> important

The over-optimizing paradox

- "Good enough" may be good enough
- Prediction critical for system success or just an gimmick?
- Better predictions may come at excessive costs
  - Data is often the bottleneck
  - Cost of producing more data (labeling, infra, collection, …)
- Better user interface ("experience") may mitigate many problems
  - Explain decisions to users with Explainable AI (XAI)
- Use only high-confidence predictions?

Critical thinking when doing the project definition

Ask the right questions - make sure you have a solid use case before you start building anything.

- **Baseline**: What is the performance of an alternative to ML? How do simple heuristics or human guess-predictions perform?
- **Probabilistic**: ML is by definition not deterministic. Are probabilities/ranges fine for this use case? E.g. for demand forecasting the model can make errors, for self-driving cars not…
- **Precision / recall**: Are both important? If not, can I make it a success by sacrificing one? E.g. for fraud detection we can raise a warning on false positive, but cannot have false negative…
- **Interpretability**: Do we need to explain why the model makes specific decisions? If yes, can we?
- **Do not reinvent the wheel:** Are there existing open source or 3rd party solutions? Did anybody in my organisation work on something like this?

Explainable AI (XAI)

Why do we need Explainable AI?

Answers can be wrong

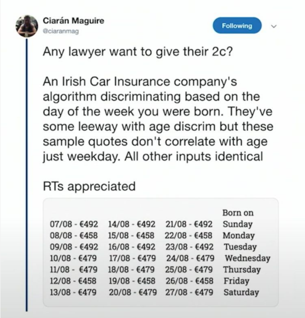
Systems like ChatGPT have produced outputs that are nonsensical (hallucinating), factually incorrect — even sexist, racist, or otherwise offensive.

Cars can crash

Uber self driving car fatally struck pedestrian in 2018.

The AI struggled to recognise the pedestrian in the dark without crosswalk.

Decisions can be biased

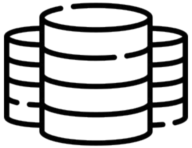


Tech entrepreneur complains that Apple Card gave him a 10x better credit score than his wife.

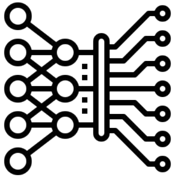
Lawyer complains that car insurance fits on the day of the week someone is born.

The concept of “black box”

Data

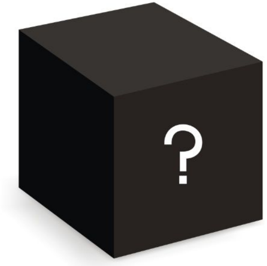


ML model



Predictions

By definition, ML models are trained to make autonomous decisions. They are not imputed with any specific rules.



It is therefore often hard to assess why the model made a specific decision.

When do you need XAI?

When AI is weaker than humans.

Transparency = finding errors
Goal = improving machines

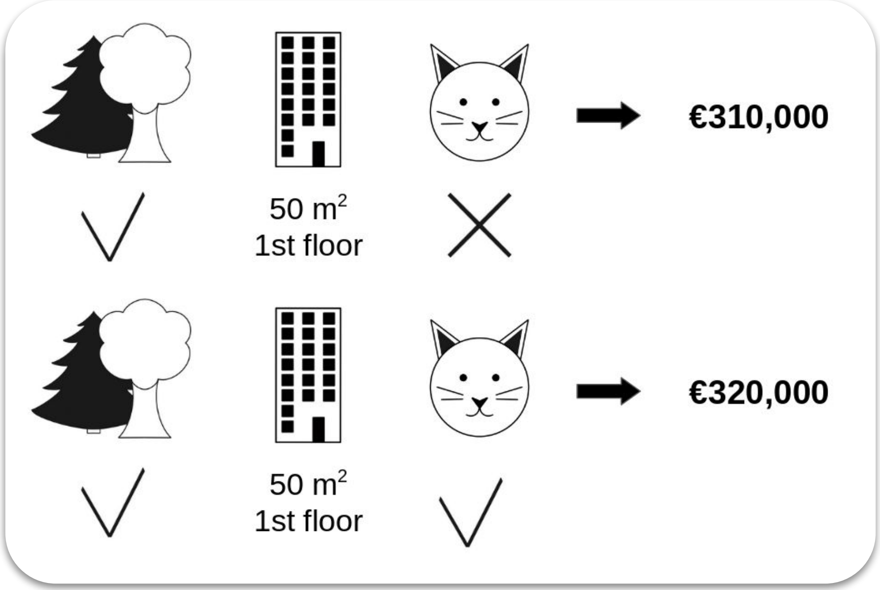
When AI is at par with humans.

Transparency = providing rationales
Goal = building trust with humans to drive adoption

When AI is stronger than humans.

Transparency = explaining a complicated concept
Goal = teaching humans

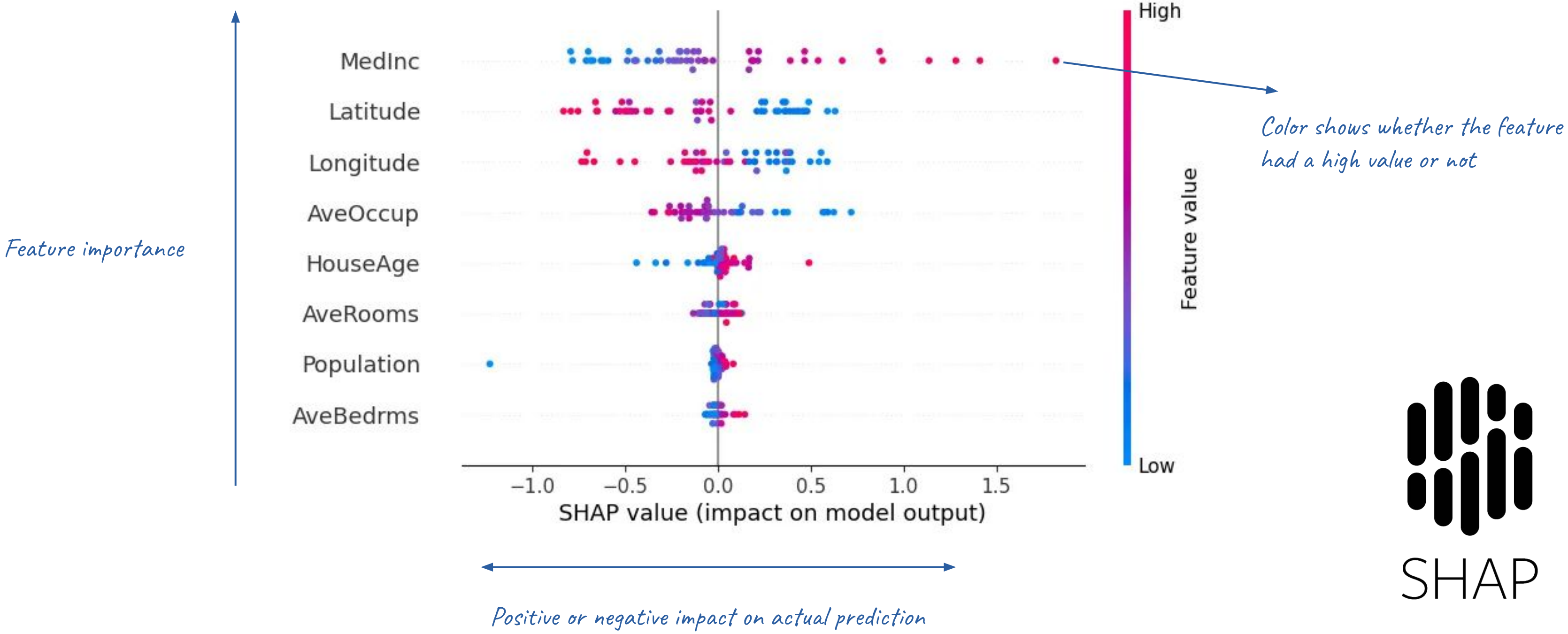
Shapley values explain the impact of a feature on a model's decision based on game theory



A prediction can be explained by assuming that each feature value of the instance is a "player" in a game where the prediction is the payout. Shapley values – a method from coalitional game theory – tells us how to fairly distribute the "payout" among the features.

Lundberg, Scott M., and Su-In Lee. "A unified approach to interpreting model predictions." Advances in neural information processing systems 30 (2017).

Example of Shapley values for house prices

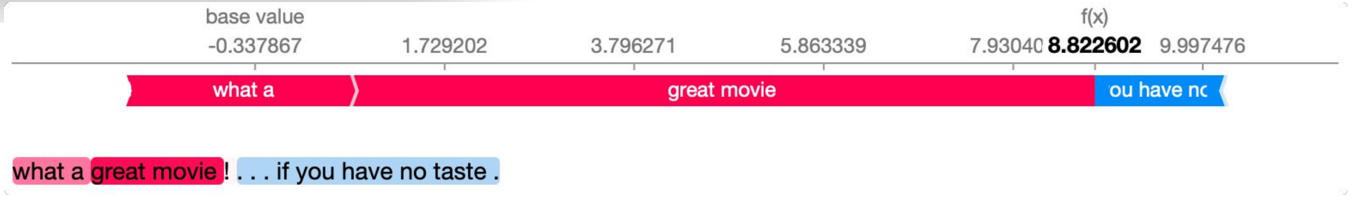


SHAP

Lundberg, Scott M., and Su-In Lee. "A unified approach to interpreting model predictions." Advances in neural information processing systems 30 (2017).

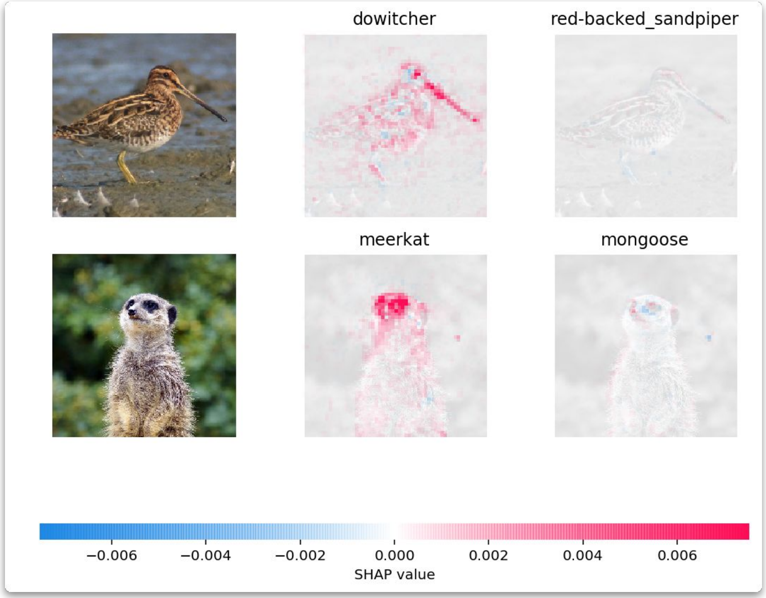
Example of Shapley values with a transformers model

```python
import transformers
import shap

# load a transformers pipeline model
model = transformers.pipeline('sentiment-analysis', return_all_scores=True)

# explain the model on two sample inputs
explainer = shap.Explainer(model)
shap_values = explainer(["What a great movie! ...if you have no taste."])

# visualize the first prediction's explanation for the POSITIVE output class
shap.plots.text(shap_values[0, :, "POSITIVE"])
```



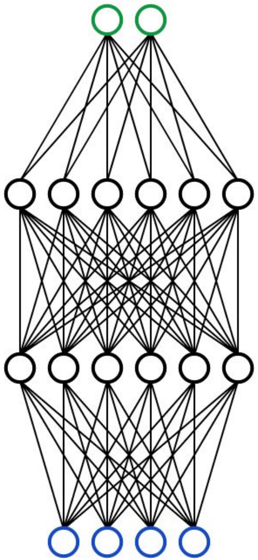
Lundberg, Scott M., and Su-In Lee. "A unified approach to interpreting model predictions." Advances in neural information processing systems 30 (2017).

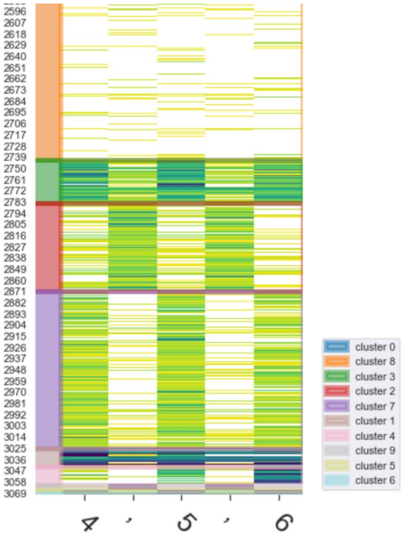
Shapley values to build a Saliency Map for a CV model in Keras

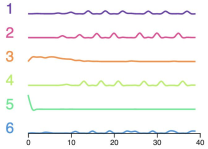


https://github.com/slundberg/shap#deep-learning-example-with-gradientexplainer-tensorflowkeraspytorch-models

Neuron Activation and Factor Analysis look at which part of your Neural Network gets activated.



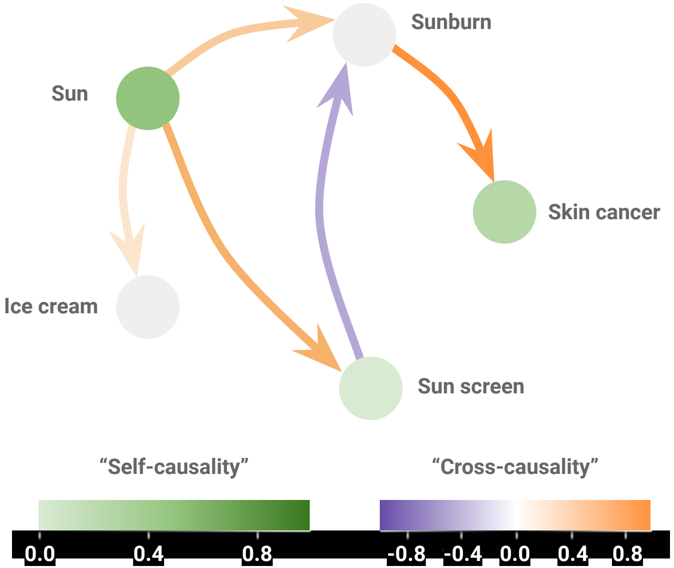




https://jalammar.github.io/explaining-transformers/

XAI also enables root cause analysis by separating correlation and causal effects.

- Getting the data depicting the problem you want to solve
  - More and finer-grained data is better.
- Measuring correlation and causal effects between all variables.
  - Quantify effect between sunscreen and sunburns.
- Creating a causal graph.
  - Get an overall overview of the problem.
- Analyse learnings and insights together with your experts
  - Investigate and validate new insights



PCMCI analysis

Wrap-up

Lecture summary

Topic	Concepts	To know for…	
		Project	Exam
Use case deep dives	• Real-estate valuation assistant • Rug cutting detection • Data Driven Sales		
Project phases & challenges	• Different phases (POC, MVP, in production, …) • Challenges		
Project definition framework	• Framework to identify, refine, prioritise and define use cases • Product design template	Yes	Yes
Explainable AI (XAI)	• What is XAI • How it can enable ML systems • Why it matters		

Project objective for sprint 1

Define the use case you will be tackling

Week	Work package	Requirement
W01	Pick a **team** (3-5 people) • Try to mix skills and experience • If you didn't find one let one of the teachers know and we'll allocate you to one	Required
W01	**Select** a use case Source options • Previous course • https://www.kaggle.com/datasets • … Make sure to pick a use case where **data is available**.	Required
W01	**Define** your use case with the ML Canvas template page	Required
W02	Setup **communication channel** (Discord, Trello board (optional))	Required
W02	Setup a **code** versioning **repository**	Required
W02	Find a cool name for your team ✨	Required

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What makes a good dataset/project for this course

The focus will *not* be on the modeling itself but rather on the system that comes around the model.

Qualities of a good dataset/project:

- Easily available data
- Real world application or value added
    - At the end you will be able to deploy your model and literally make it publicly usable
- ML model should not be challenging
- Ideally some value in retraining and maintaining


MADE IT THROUGH THE LECTURE
SEE YOU NEXT WEEK !
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