

# Explanation by Example

The OptaPlanner way

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# Business Automation

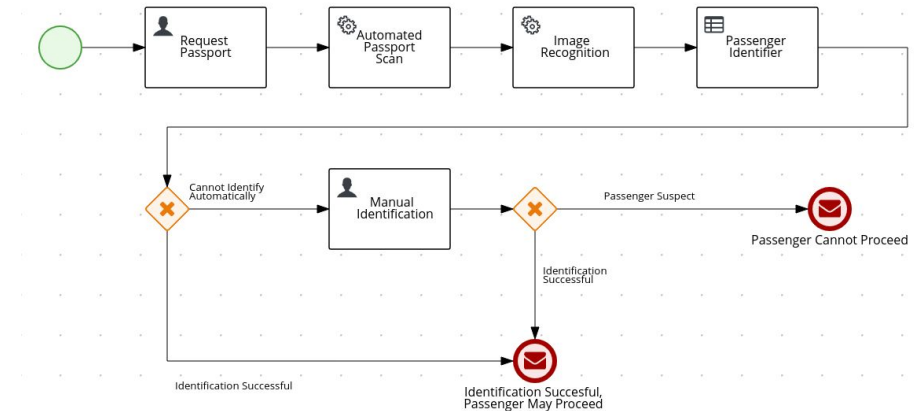
## Decision



Automatically processed? (Decision Table)

F	Calculate Trip risk (number)	Image score (number)	Automatically processed? (boolean)	Description
1	>0.8	-	false	Trip risk is too high
2	-	<0.7	false	Passport image is too different
3	-	-	true	Fine to proceed

## Process



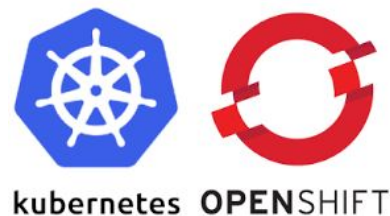
Vehicle Routing

## Mathematical Optimization



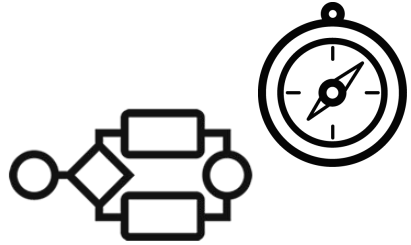
# Next-gen Cloud-Native Business Automation

Cloud-Native Business Automation for building intelligent applications,  
backed by battle-tested capabilities

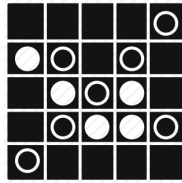


# Cloud-Native Business Automation

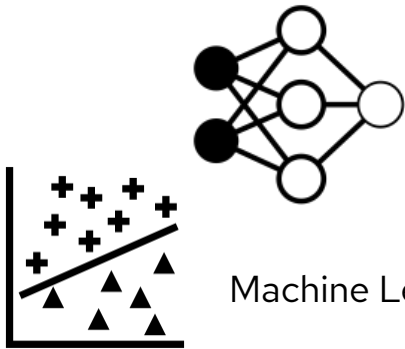
## Knowledge as a Service



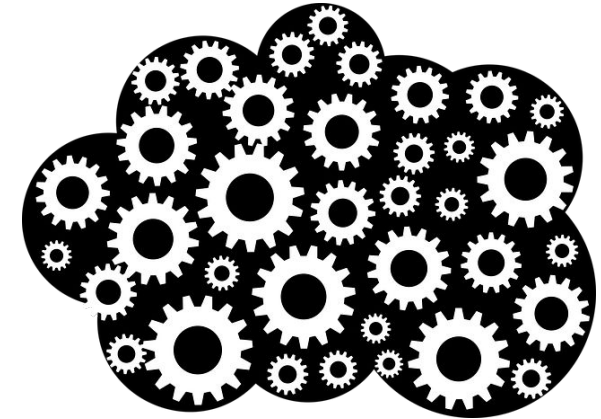
Workflow and Digital Decisioning



Mathematical Optimization



Machine Learning



**Knowledge as a Service**

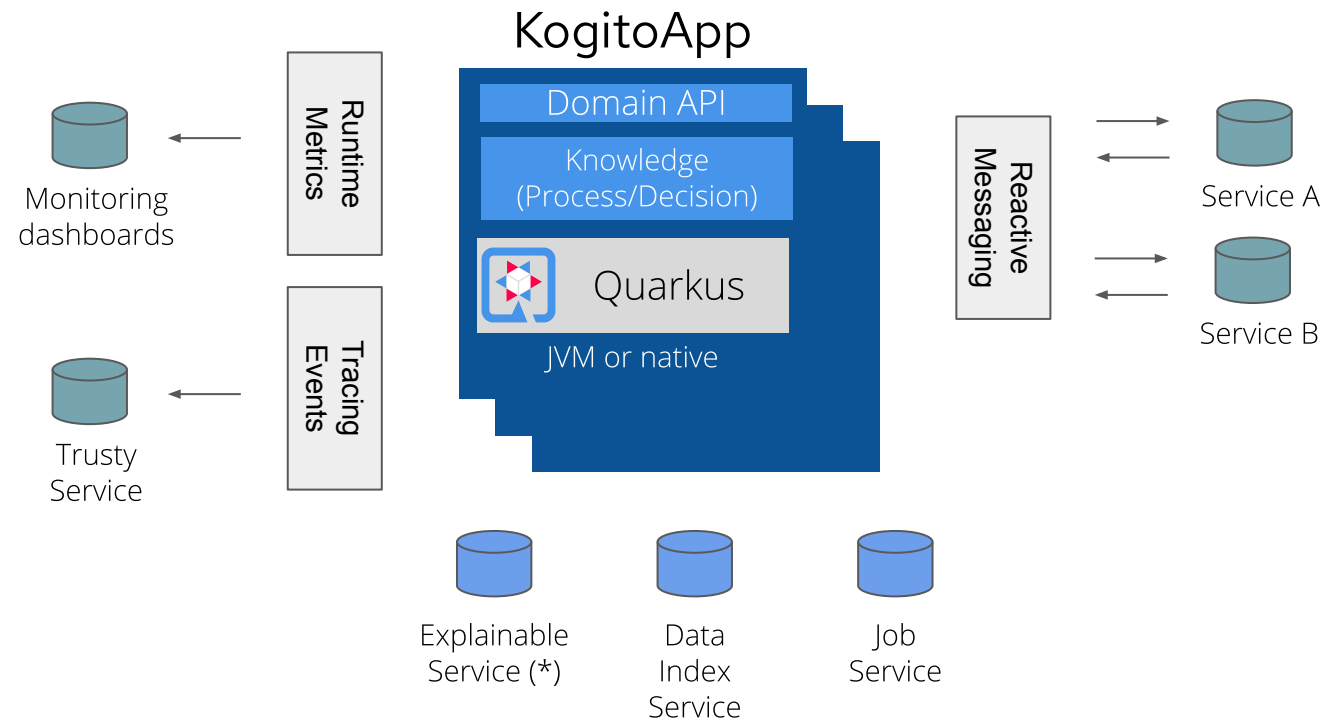
# TrustyAI

Offer value-added services for Business Automation.

- **Runtime Monitoring Service**
  - dashboard for business runtime monitoring
- **Tracing and Accountability Service**
  - extract, collect and publish metadata for auditing and compliance
- **Explanation Service**
  - XAI algorithms to enrich model execution information



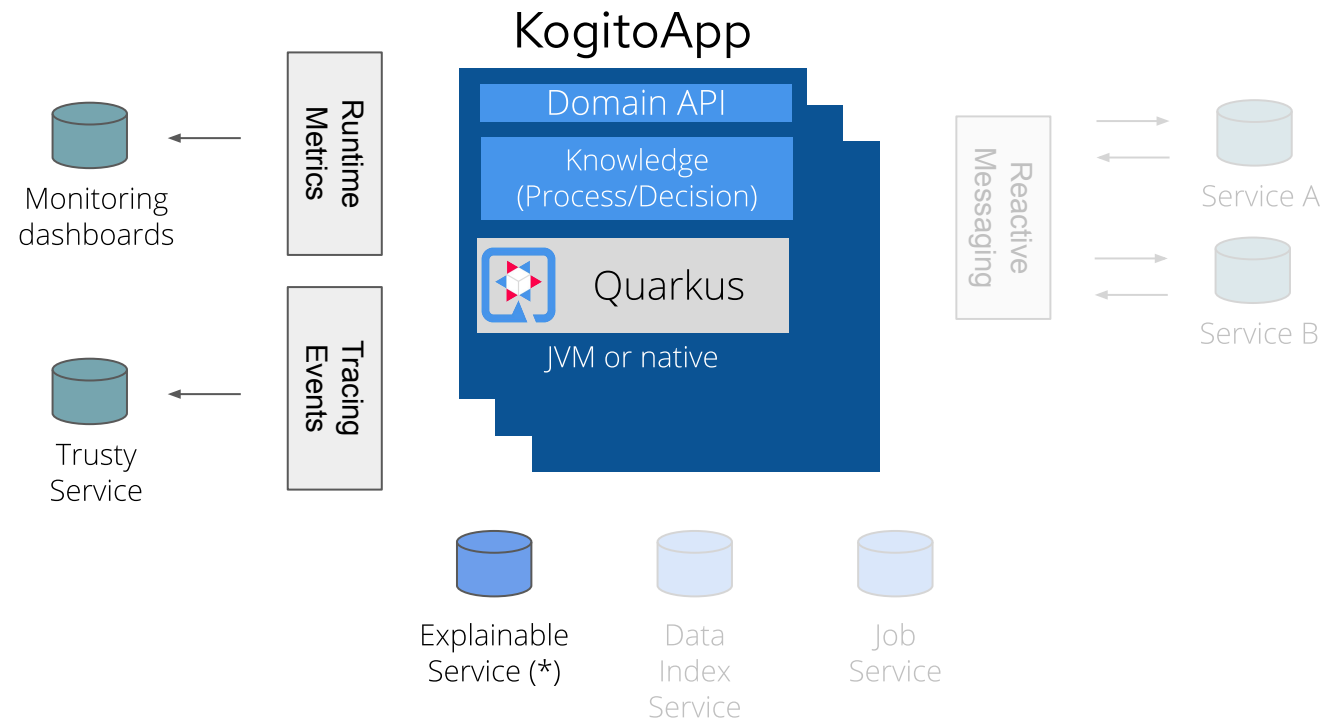
# Runtime Ecosystem



OpenShift

(\*) Kogito 0.15 (~middle September)

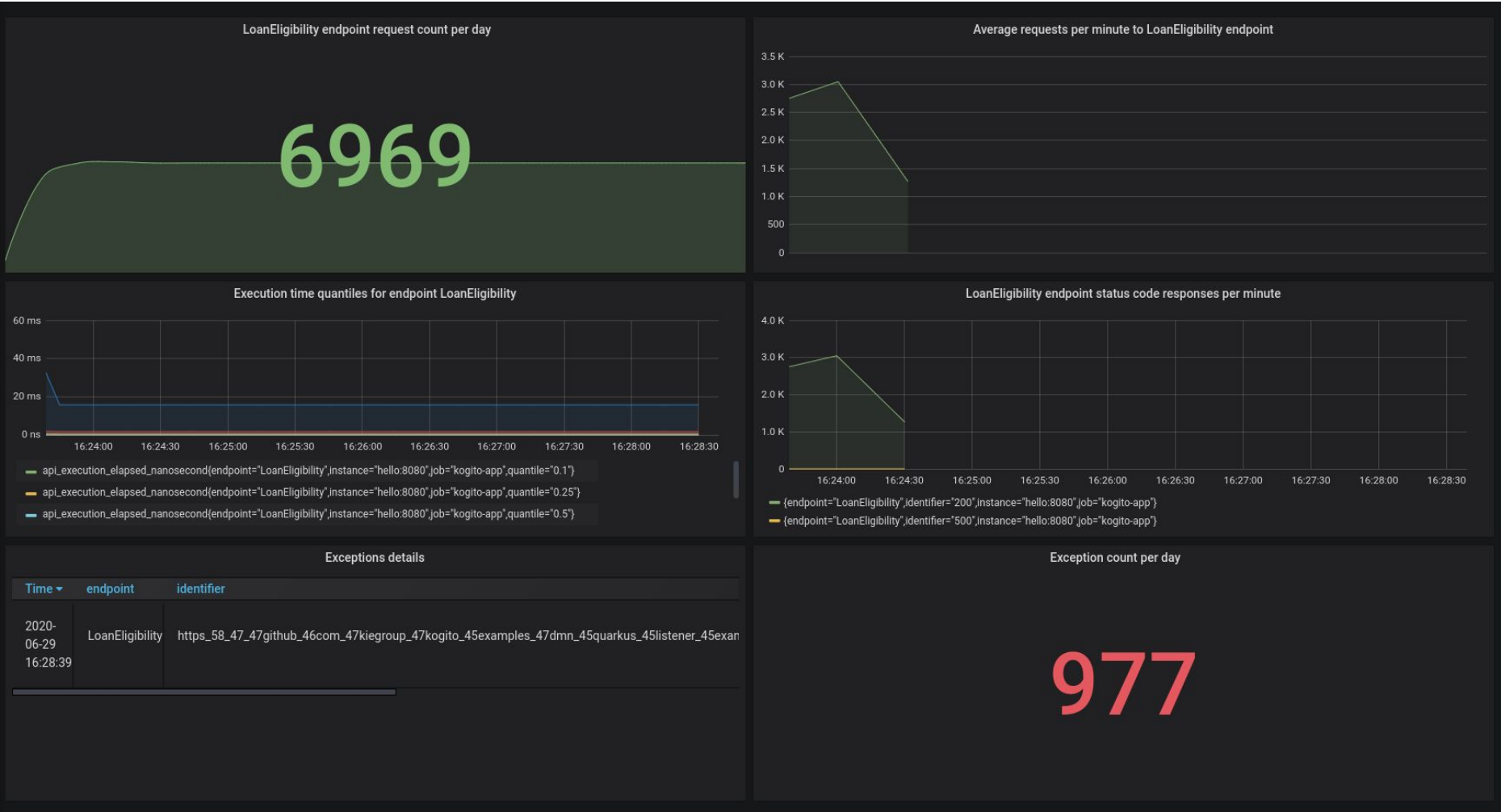
# TrustyAI Services



OpenShift

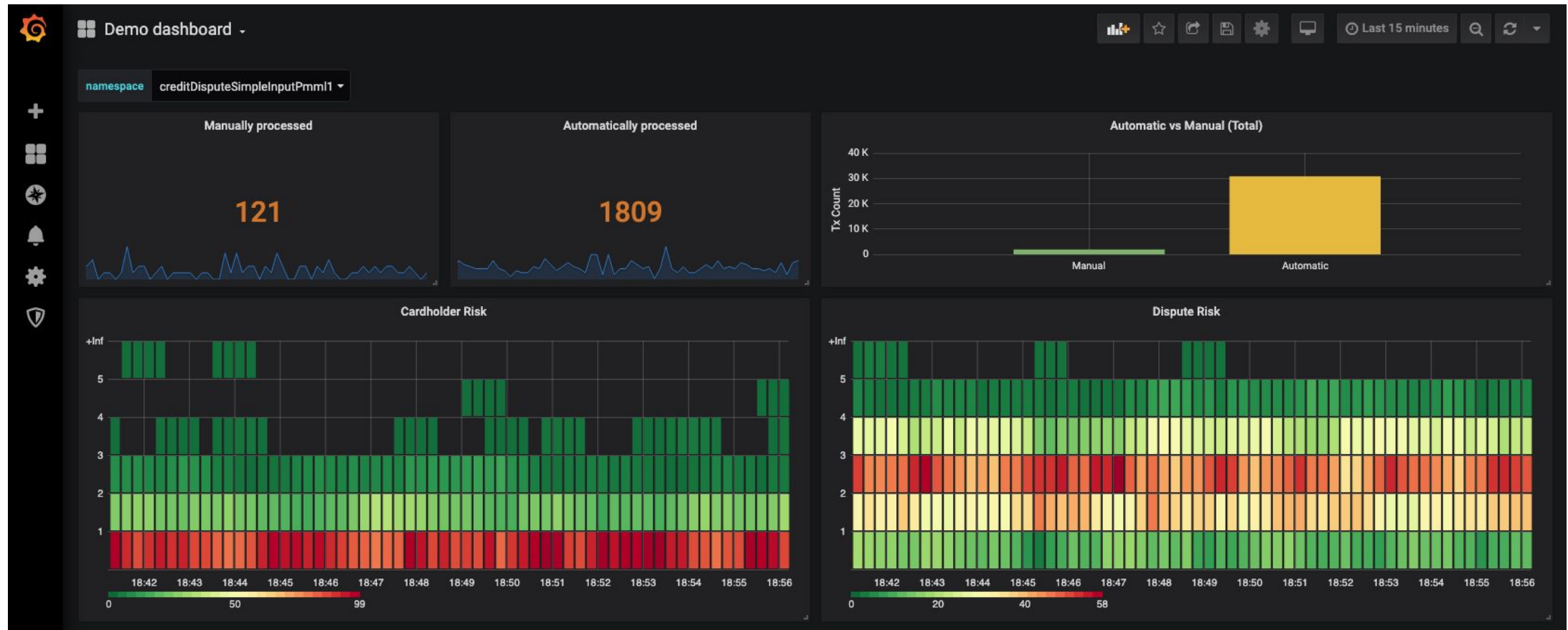
(\*) Kogito 0.15 (~middle September)

# DevOps Monitoring





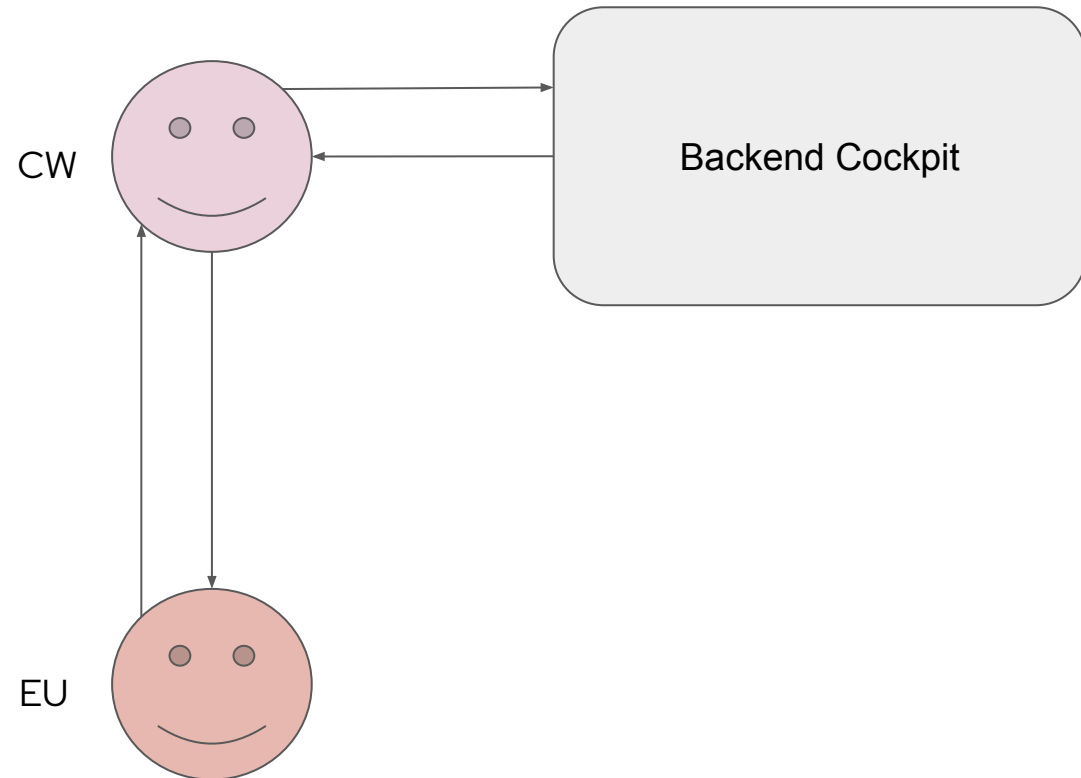
# Business Monitoring



# Use case: Credit card approval

"As a case worker (CW) I want to be able to **explain** to end user (EU) **why** that credit card request was rejected or accepted."

"As a case worker (CW) I want to provide information to my end user (EU) about **what is needed** to get it accepted."



# Trusty UI (\*)

The screenshot displays the Kogito Trusty UI interface. The top navigation bar is dark with the Kogito logo and a user profile icon. The left sidebar contains three menu items: 'Audit Investigation' (highlighted), 'Business Monitoring', and 'Operational Monitoring'. The main content area shows the breadcrumb 'Audit Investigation > ID #B2B0ED8D-C1E2-46B5-3AC54FF4BEAE-1006 > Outcomes'. Below this, the ID '# B2B0ED8D-C1E2-46B5-3AC54FF4BEAE-1006' is displayed with a green checkmark and the status 'Completed'. A sub-navigation bar includes 'Outcomes' (underlined), 'Outcomes Details', 'Input Data', and 'Model Lookup'. The 'Outcomes' section contains two white cards: 'Confidence' with a value of '0.8' and 'Approved' with a value of 'False'. Each card has a 'View Details' link with a right-pointing arrow.

Kogito

Audit Investigation > ID #B2B0ED8D-C1E2-46B5-3AC54FF4BEAE-1006 > Outcomes

ID# B2B0ED8D-C1E2-46B5-3AC54FF4BEAE-1006 ✓ Completed

Outcomes Outcomes Details Input Data Model Lookup

Outcomes

Confidence

0.8

[View Details →](#)

Approved

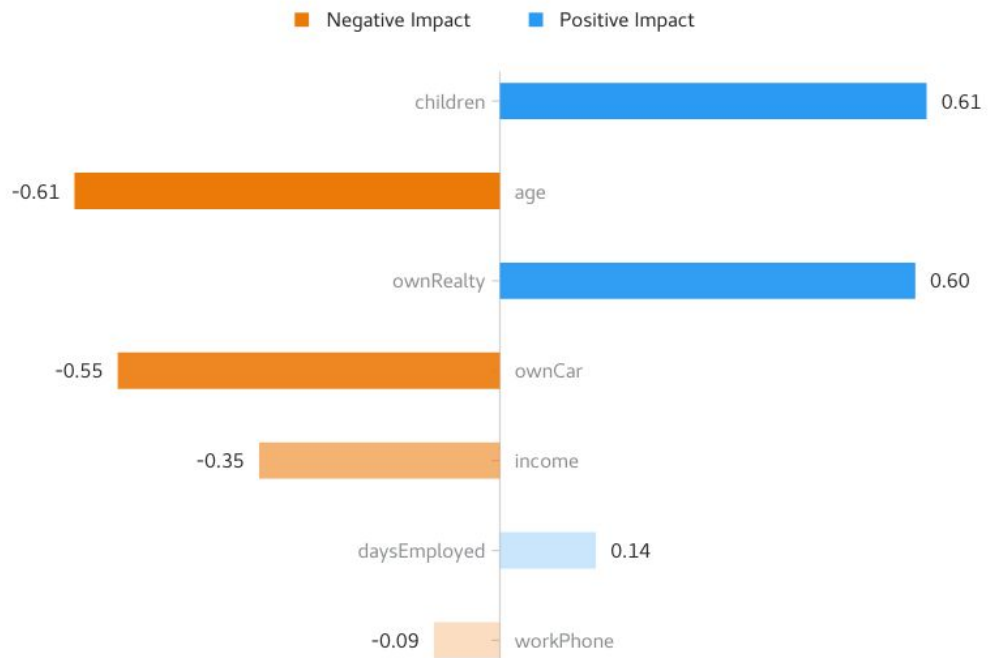
False

[View Details →](#)

# Trusty UI (\*)

## Explanation

### Features Score Chart



### Features Weight

Positive Weight	Score
children	0.61
ownRealty	0.60
daysEmployed	0.14
Negative Weight	Score
age	-0.61
ownCar	-0.55
income	-0.35
workPhone	-0.09

# Explainability – Goals

- Establish **trust** in automated business processes
- **Transparent** decision making when black box models are involved
  - More fine grained **understanding** of specific **predictions**
  - Coarse grained **model behaviour** understanding
- **Accountability**
  - Track changes in model behaviour across versions

# My black box model is...



## Transparent

A model is considered to be transparent if by itself the model makes a human understand how it works without any need for explaining its internal structure or algorithms



## Explainable

A model is explainable if it provides an interface with humans that is both accurate with respect to the decision taken and comprehensible to humans



## Trustworthy

A model is considered trustworthy when humans are confident that the model will act as intended when facing a given problem

# The right explanation to the right stakeholder

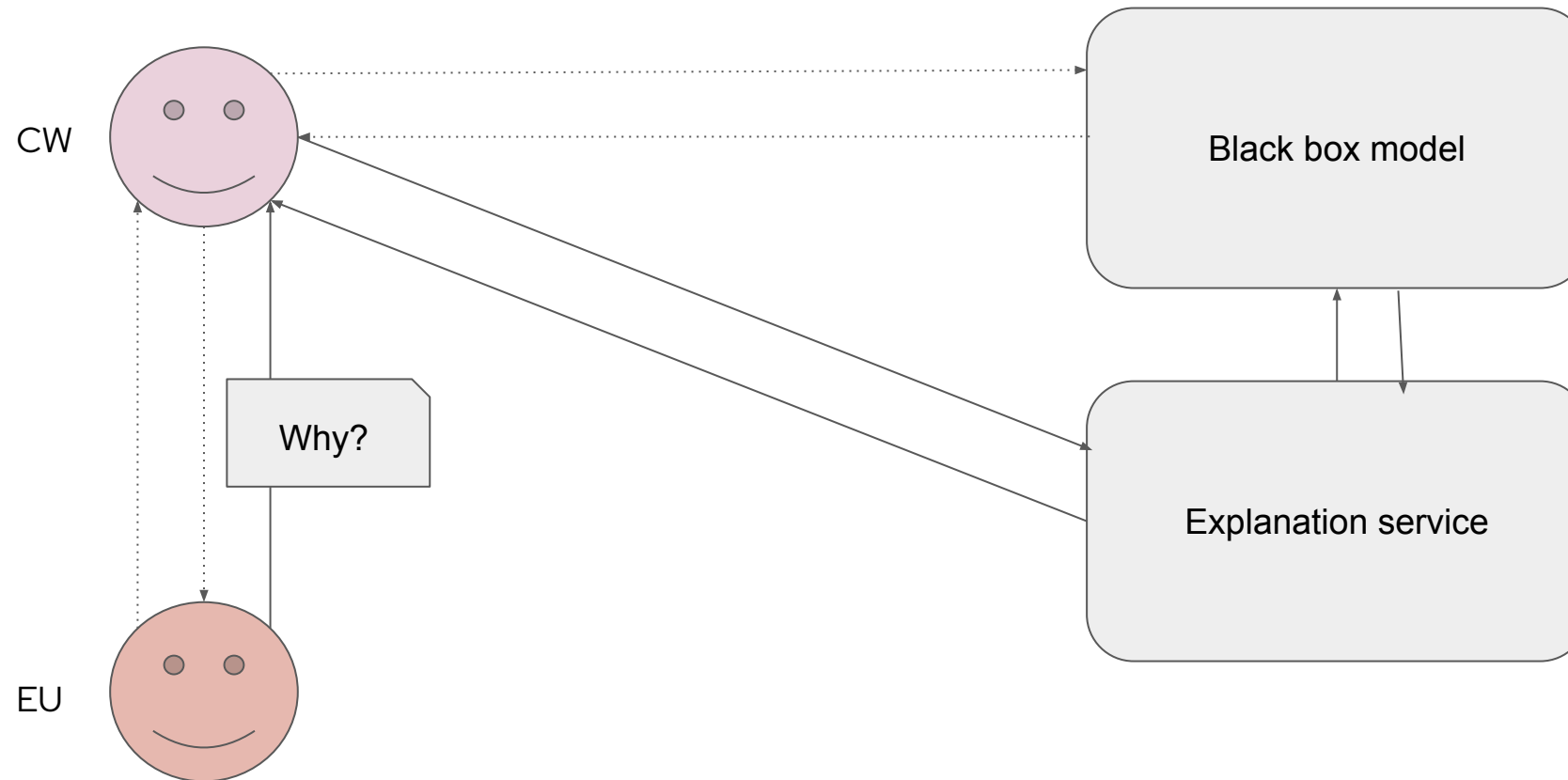
- **Case worker**
  - Good domain knowledge, case by case
  - No technical knowledge
- **Compliance worker**
  - Good high level domain knowledge
  - No technical knowledge
- **Data scientist**
  - No/limited domain knowledge
  - Good technical knowledge

# The right explanation to the right stakeholder

- **Case worker**
  - Needs explanations on a case by case basis to support end users
    - Local explanations
- **Compliance worker**
  - Needs explanation from a high level perspective (regulations, business objectives, etc.)
    - Global explanations
- **Data scientist**
  - Needs explanations to understand model behavior and debug
    - Global and local explanations



# Case worker

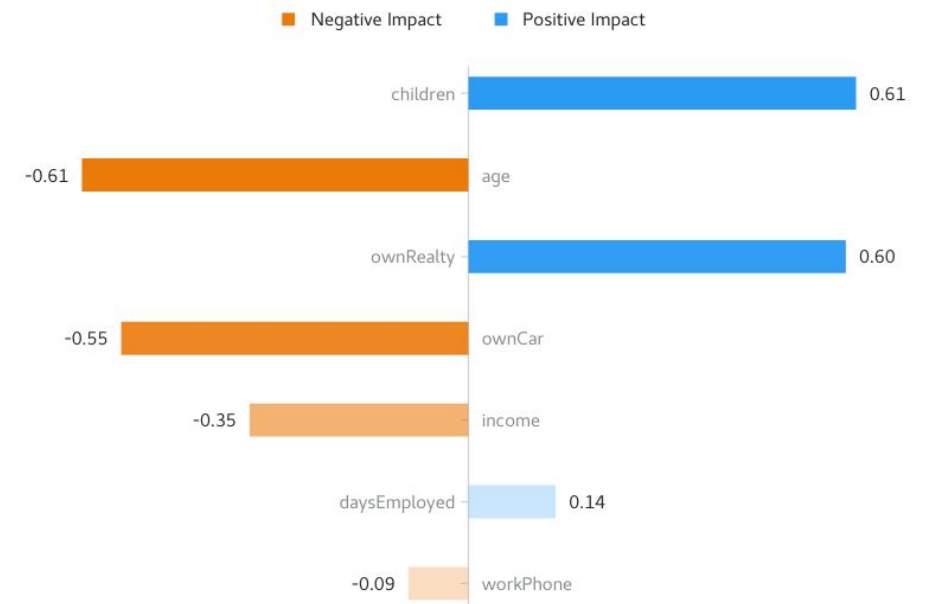


# Case worker – Why

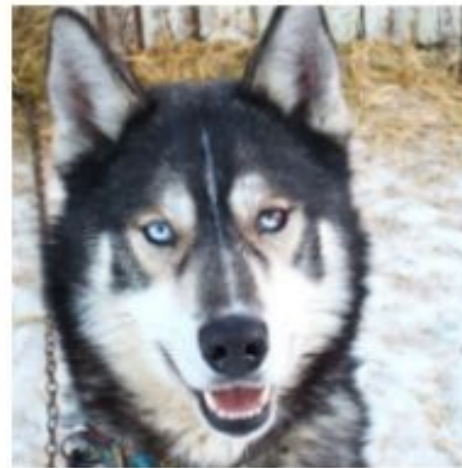
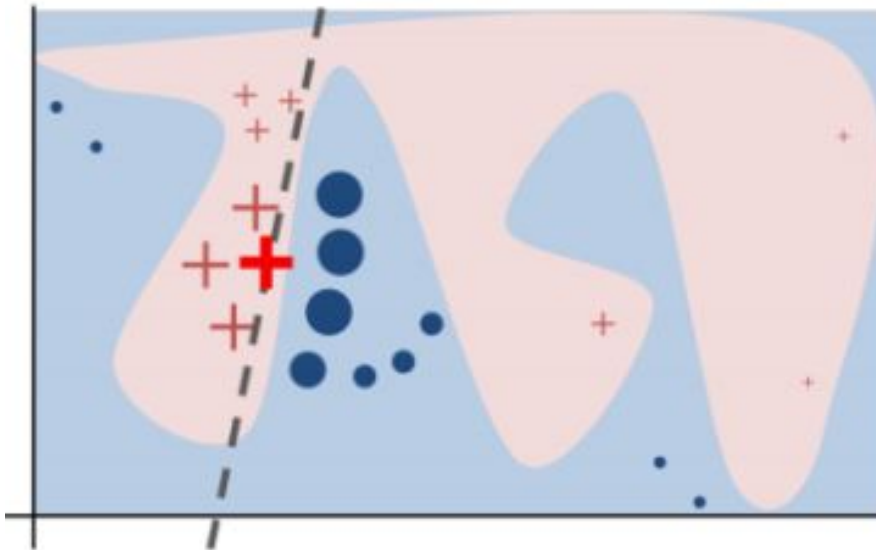
- **Need**
  - Which *inputs* does the model give more importance to decide whether to grant the credit card or not?
- **Explanation**
  - **Saliency** explanations give *feature importance* scores for a *single* prediction
    - The value of *children* plays a **positive** role for granting the credit card
    - The value of *age* plays a **negative** role for granting the credit card

## Explanation

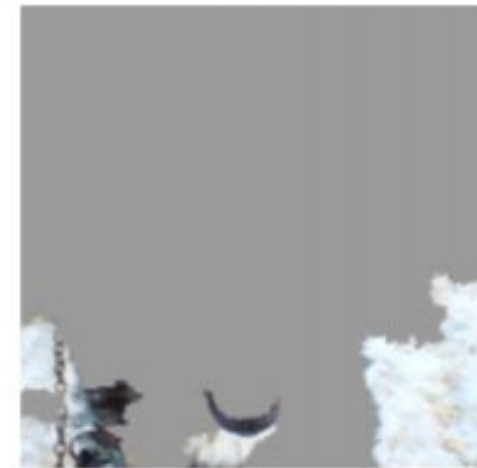
Features Score Chart



# LIME



(a) Husky classified as wolf



(b) Explanation

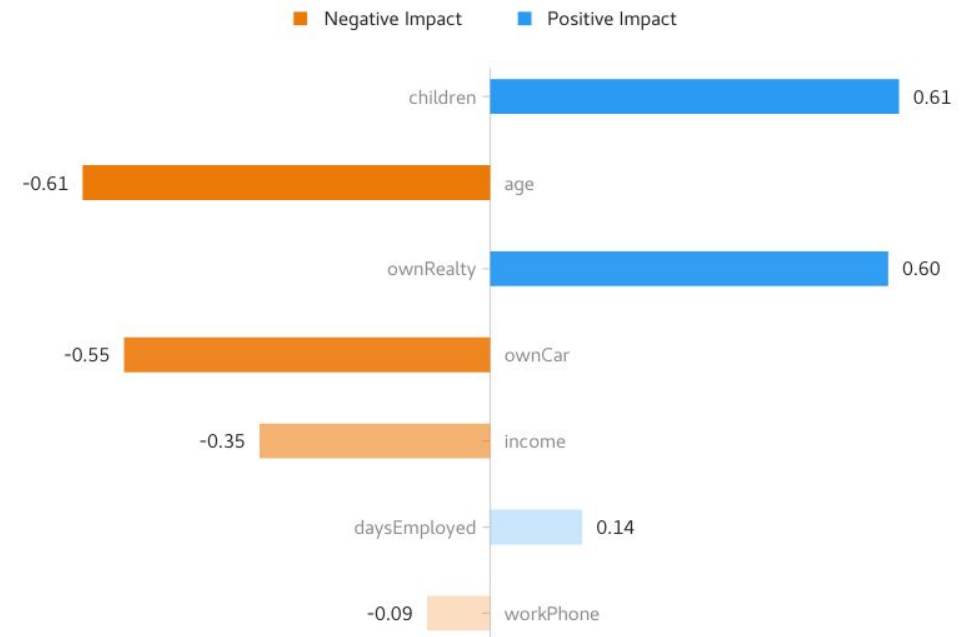
- Ribeiro, Marco Tulio, Sameer Singh, and Carlos Guestrin. "Why should I trust you?: Explaining the predictions of any classifier." Proceedings of the 22nd ACM SIGKDD, 2016

# LIME (\*)

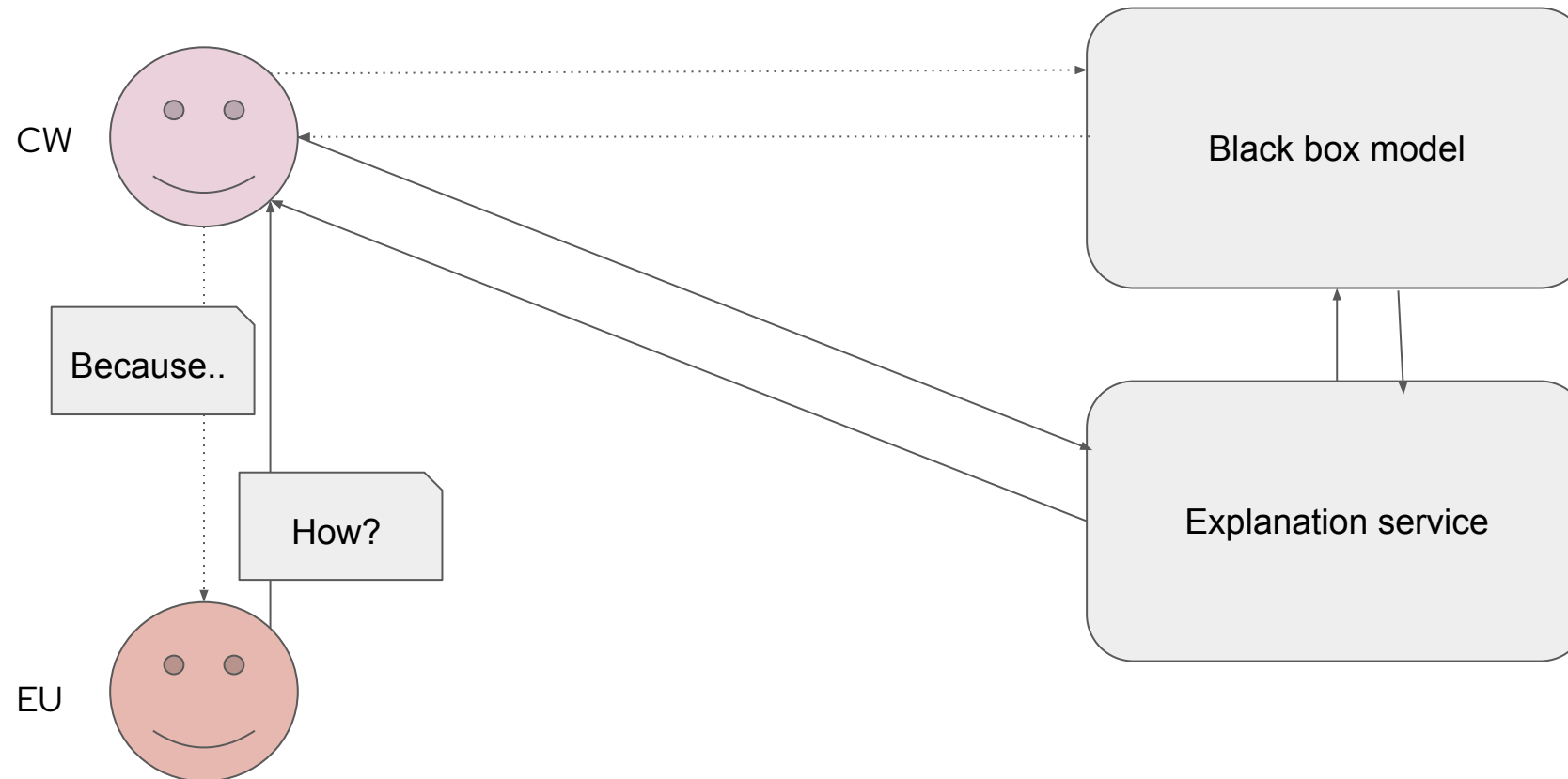
- LIME tests what happens to the prediction when you provide *perturbed* versions of the input to the black box model
- Trains an **interpretable** model (e.g. a linear classifier) to separate perturbed data points by label
- The *weights* of the linear model (one for each feature) are used as **feature importance** scores

## Explanation

### Features Score Chart



# Case worker



# Case worker – How

- **Need**
  - What should the end user *change* to get the credit card (similar input, flipped prediction) ?
- **Explanation**
  - **Exemplar** explanations provide explanations for single predictions by means of **examples** (in the input space)
    - **Counterfactual explanations** provide examples that
      - Have a *desired* prediction, according to the black box model
      - Are as *close* as possible to the original input
    - How should the user change its inputs in order to get a formerly rejected credit card request granted ?

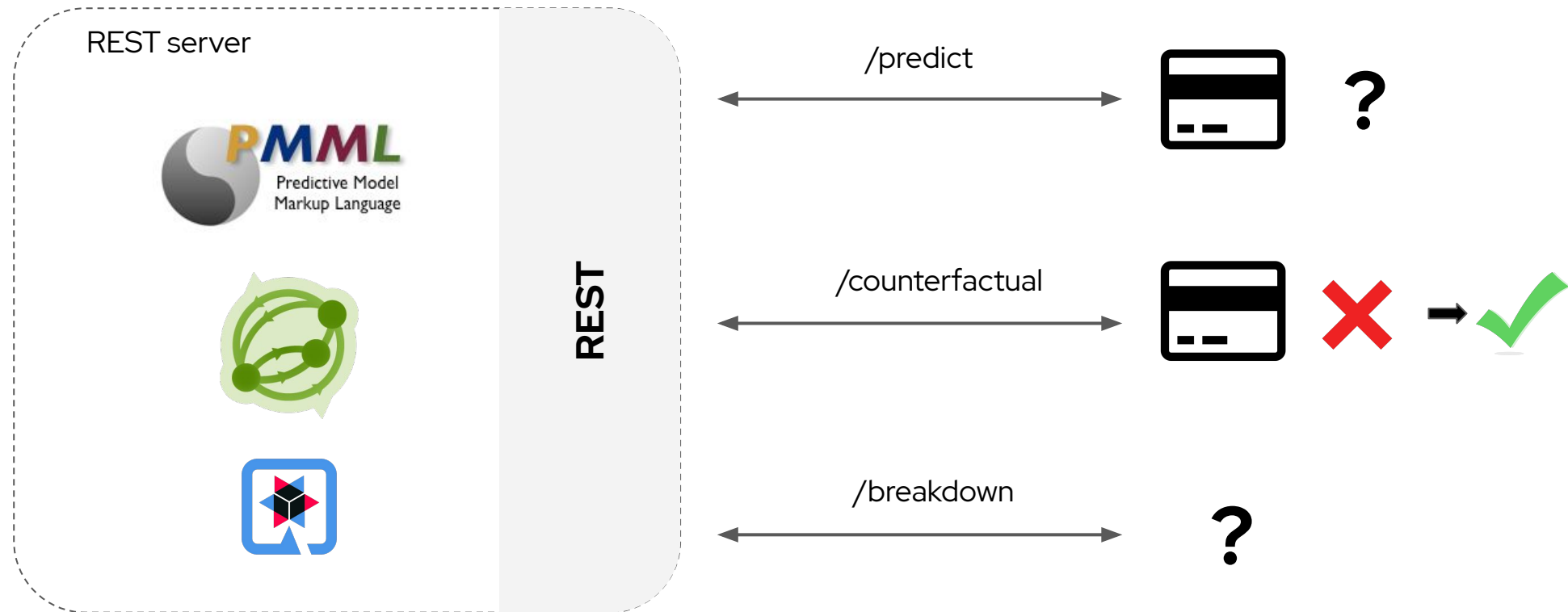
# Counterfactual explanations

- Usually work by **minimizing** two cost functions
  - **Input cost**
    - representing the distance between the original input and a new input
  - **Target cost**
    - representing the distance between the desired output and the output generated by querying the model with the new input
- Huge **search space**
  - High dimensional inputs
  - Numerical features
  - Out of distribution problems
- **Hard constraints** make the problem worse
  - Some things cannot be (easily) changed by the end user

# Demo

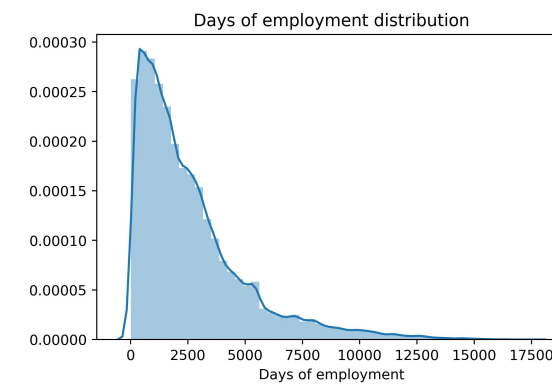
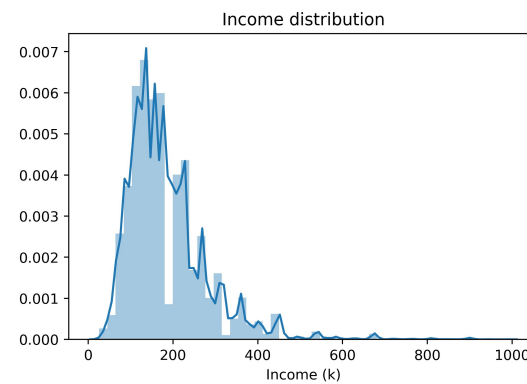
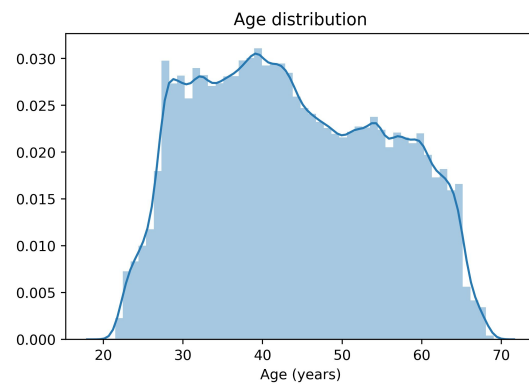


# Demo architecture



# Training dataset

age	income	# children	employment days	owns realty	has work phone	owns car
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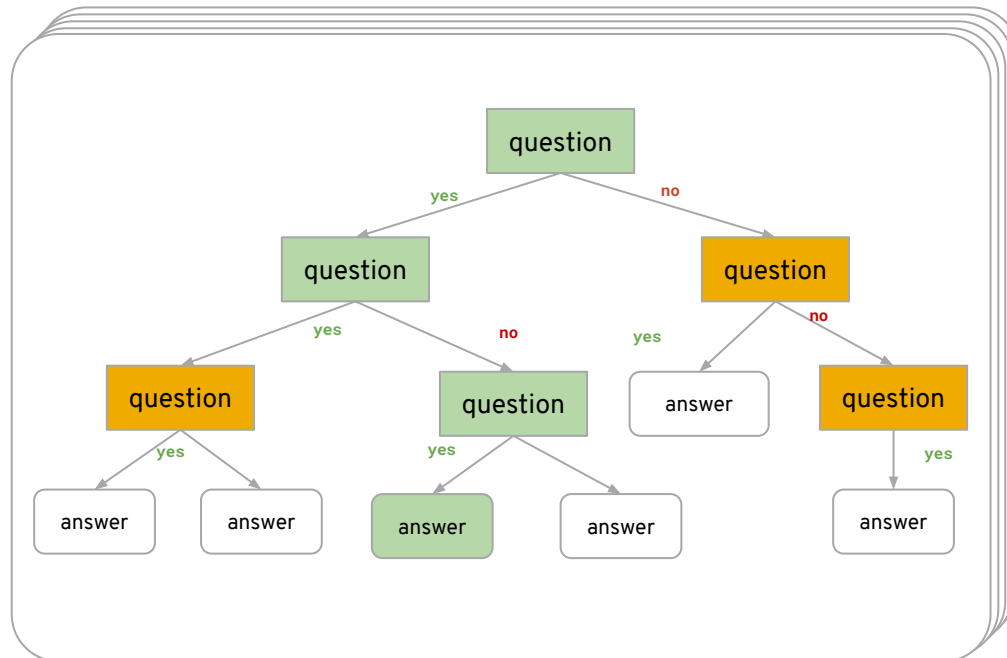


# Building the predictive model

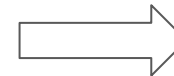
age	income	# children	employment days	owns realty	has work phone	owns car
-----	--------	------------	-----------------	-------------	----------------	----------



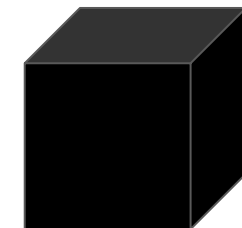
Random forest classifier



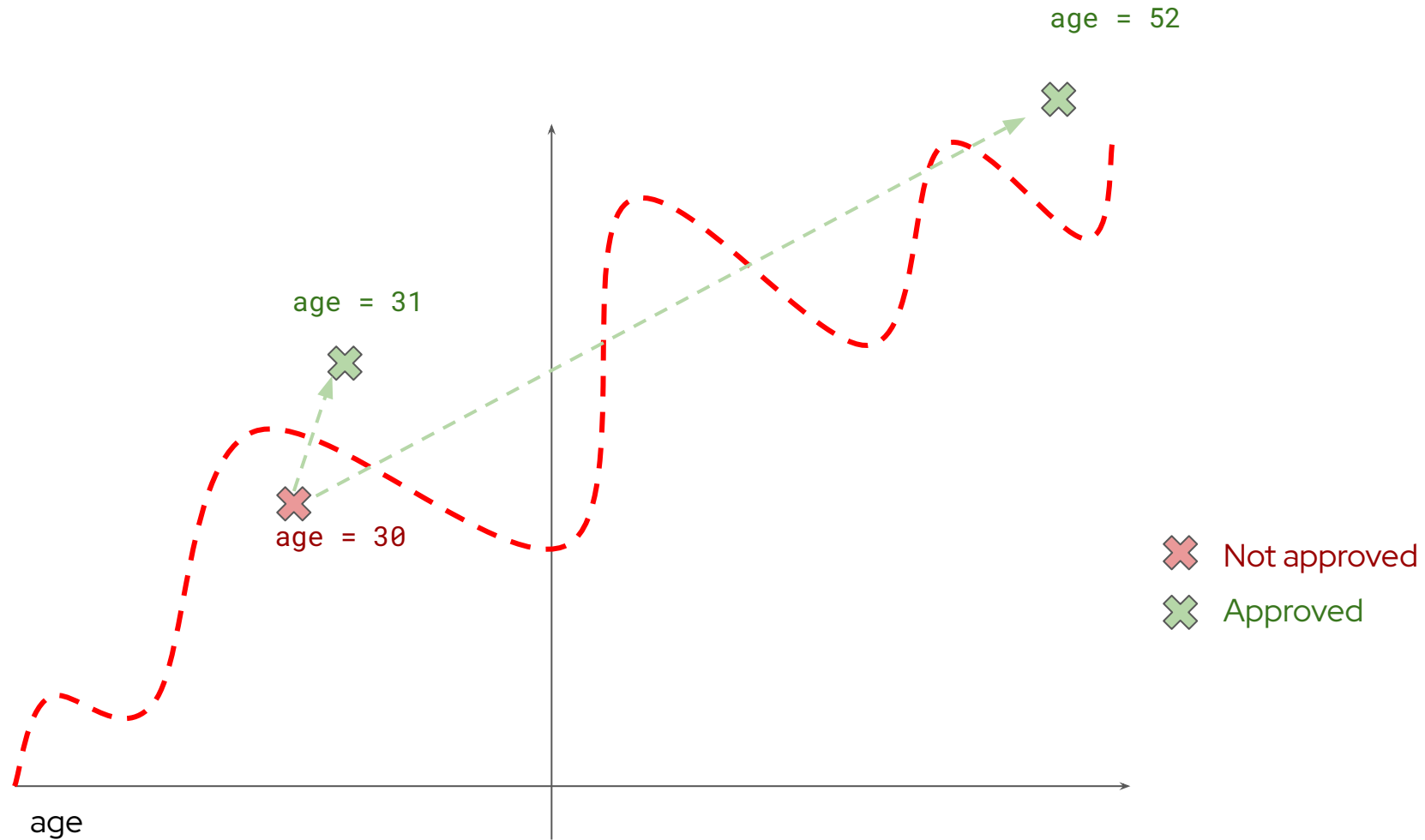
sklearn2pmml



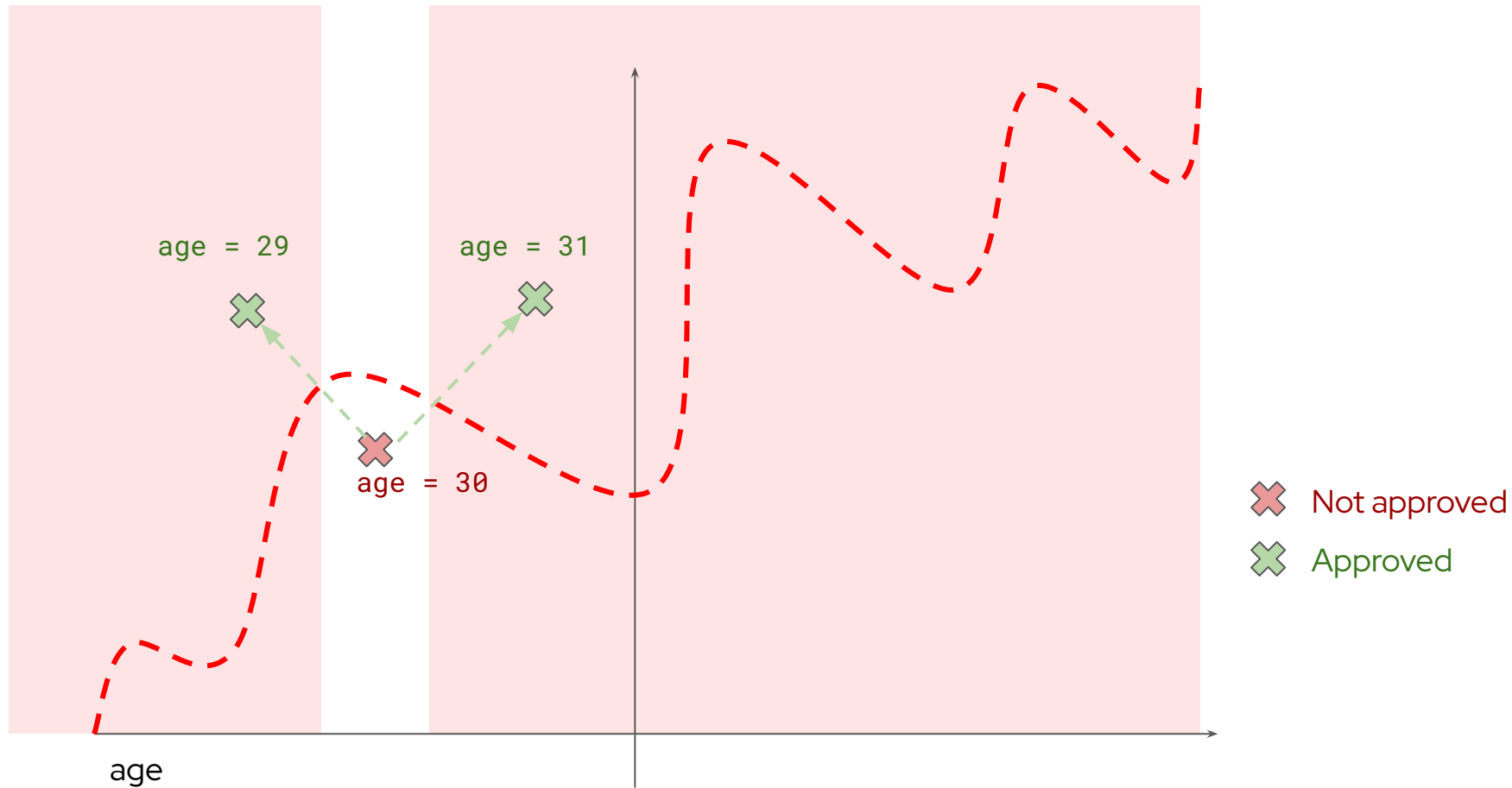
PMML



# Domain search space

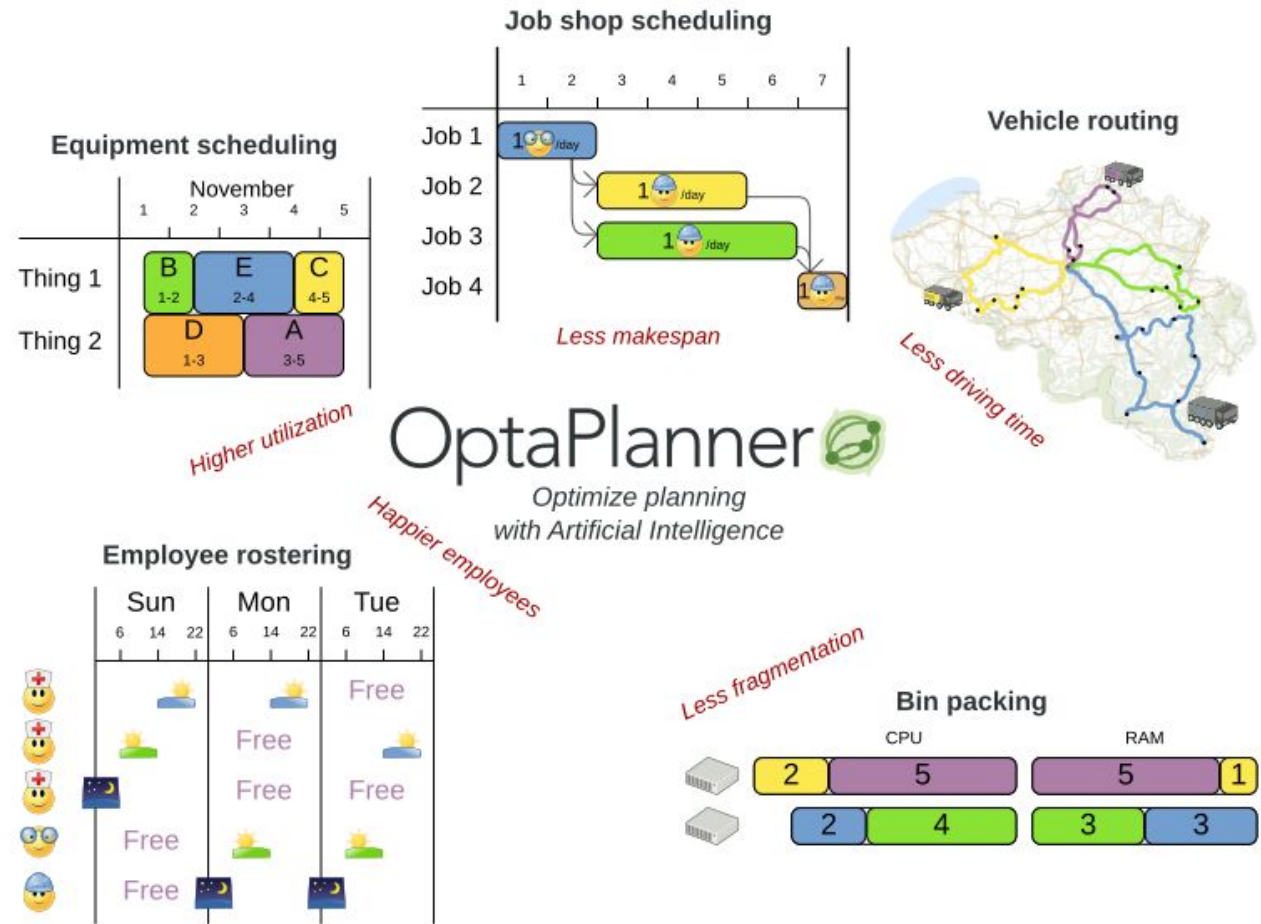


# Fixed inputs constraint

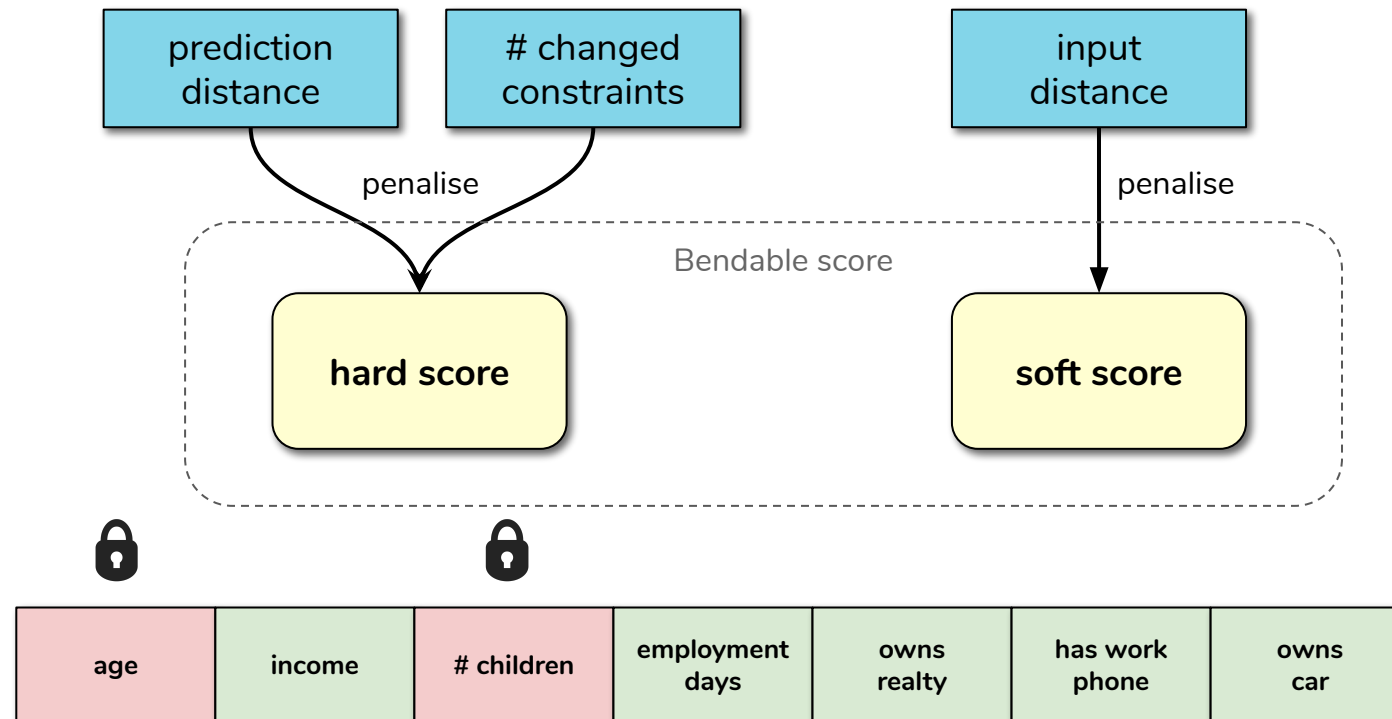


# OptaPlanner

- Open source
- Battle-tested constraint solver
- Express complex constraints



# Counterfactual solution scoring



# Defining constraints and domain

## Constraint streaming API

```
public class ApprovalConstraintsProvider implements ConstraintProvider{

    private Constraint changedAge(ConstraintFactory constraintFactory) {
        return constraintFactory
            .from(CreditCardApprovalEntity.class)
            .filter(entity -> !entity.getAge().equals(Facts.input.getAge()))
            .penalize(
                "Changed age",
                BendableBigDecimalScore.ofHard(
                    HARD_LEVELS_SIZE, SOFT_LEVELS_SIZE, 1, BigDecimal.valueOf(1)));
    }
}
```

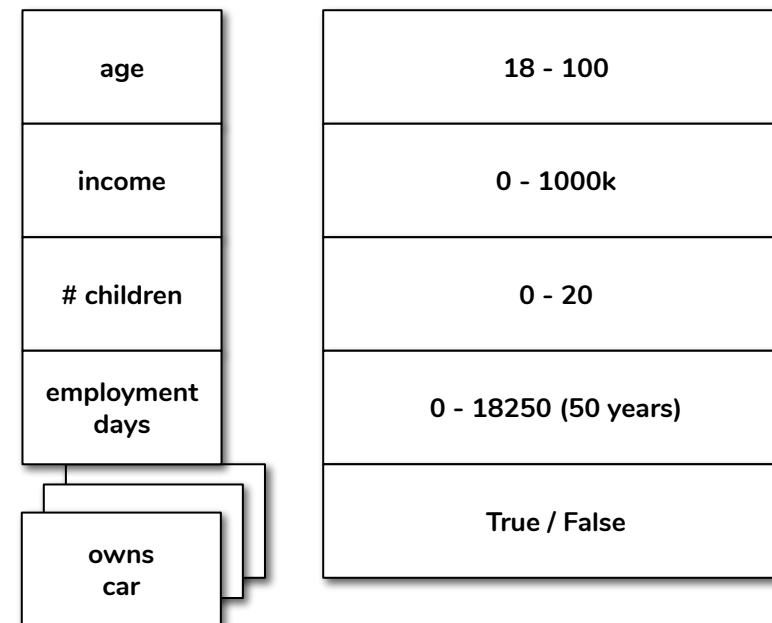
## Planning variables

```
@PlanningVariable(valueRangeProviderRefs = {"ageRange"})
public Integer getAge() {
    return age;
}

@PlanningVariable(valueRangeProviderRefs = {"incomeRange"})
public Double getIncome() {
    return income;
}

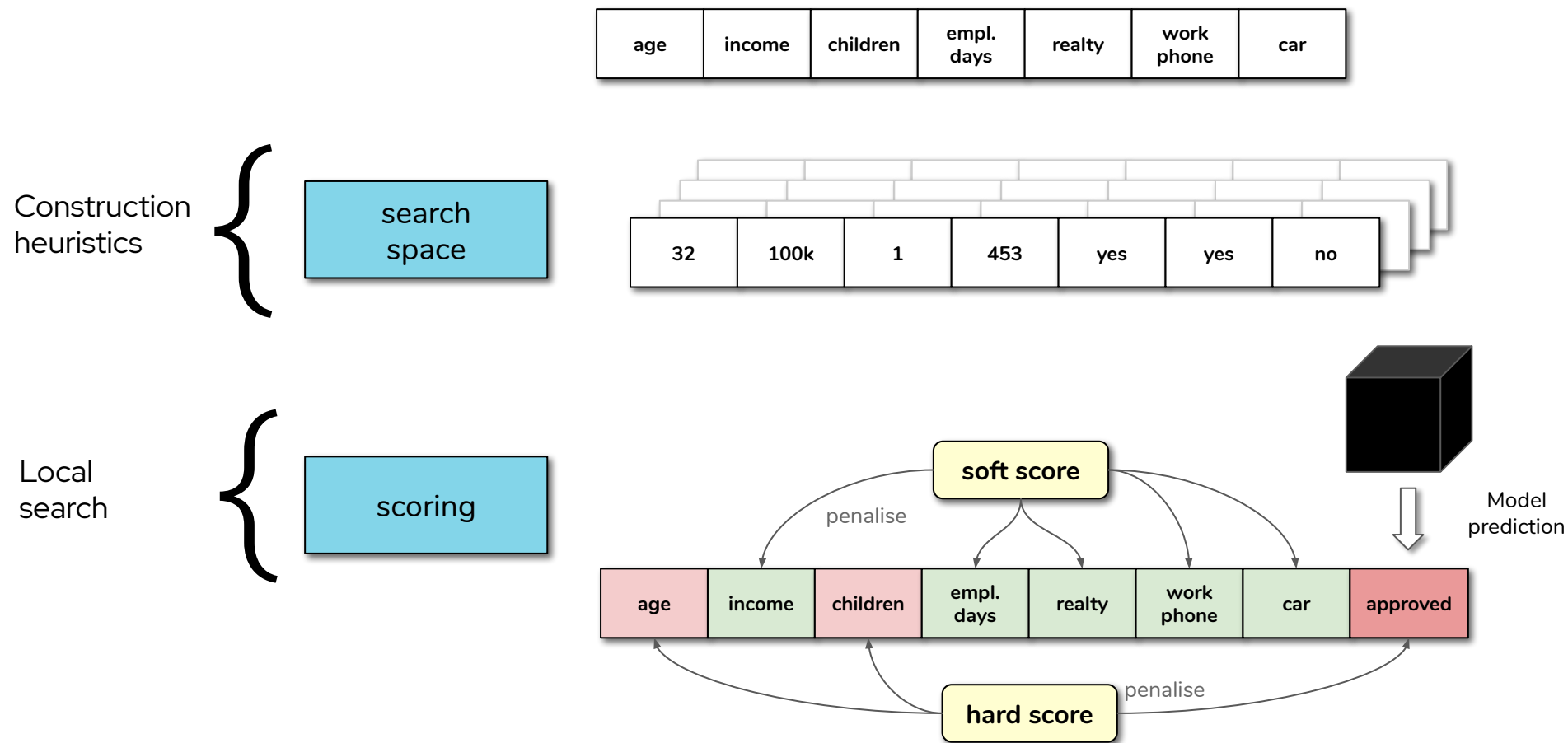
@PlanningVariable(valueRangeProviderRefs = {"childrenRange"})
public Integer getChildren() {
    return children;
}

...
```

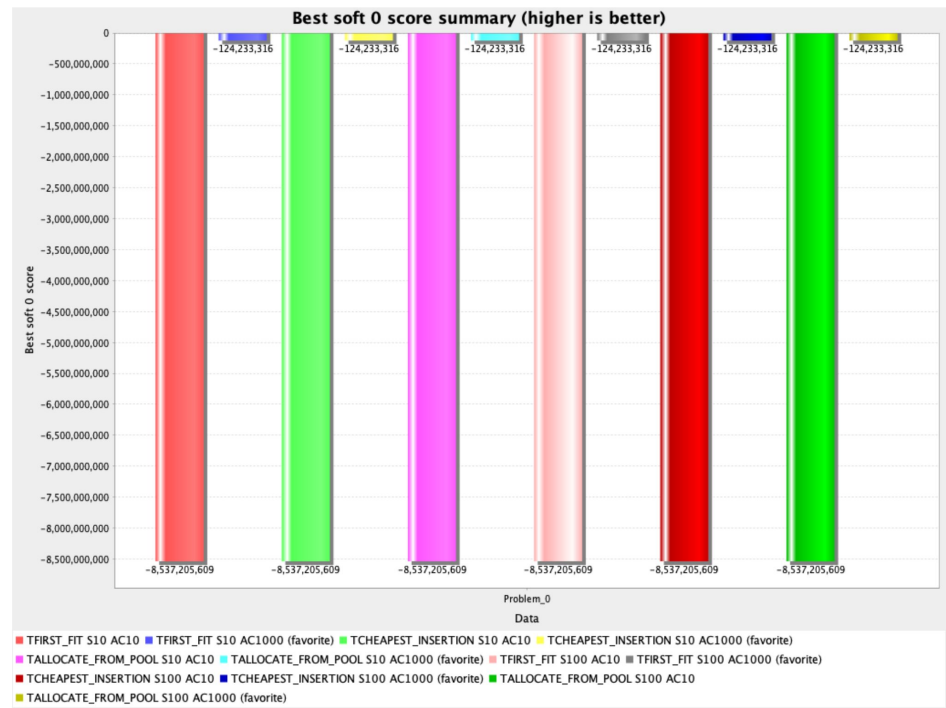




# Searching for counterfactuals



# Benchmarking



Solver	Total	Average	Standard Deviation	Problem	
				Problem_0	Problem_0
TFIRST_FIT S10 AC10 6 1	[0/-1]hard /[-8537205609.0]soft	[0/-1]hard /[-8537205609.0]soft	0.0E0/0.0E0 /0.0E0	[0/-1]hard /[-8537205609.0]soft 0 1	
TFIRST_FIT S10 AC1000 0	[0/0]hard /[-124233316.0]soft	[0/0]hard /[-124233316.0]soft	0.0E0/0.0E0 /0.0E0		[0/0]hard /[-124233316.0]soft 0
TCHEAPEST_INSERTION S10 AC10 6 1	[0/-1]hard /[-8537205609.0]soft	[0/-1]hard /[-8537205609.0]soft	0.0E0/0.0E0 /0.0E0		
TCHEAPEST_INSERTION S10 AC1000 0	[0/0]hard /[-124233316.0]soft	[0/0]hard /[-124233316.0]soft	0.0E0/0.0E0 /0.0E0		
TALLOCATE_FROM_POOL S10 AC10 6 1	[0/-1]hard /[-8537205609.0]soft	[0/-1]hard /[-8537205609.0]soft	0.0E0/0.0E0 /0.0E0		
TALLOCATE_FROM_POOL S10 AC1000 0	[0/0]hard /[-124233316.0]soft	[0/0]hard /[-124233316.0]soft	0.0E0/0.0E0 /0.0E0		
TFIRST_FIT S100 AC10 6 1	[0/-1]hard /[-8537205609.0]soft	[0/-1]hard /[-8537205609.0]soft	0.0E0/0.0E0 /0.0E0		
TFIRST_FIT S100 AC1000 0	[0/0]hard /[-124233316.0]soft	[0/0]hard /[-124233316.0]soft	0.0E0/0.0E0 /0.0E0		
TCHEAPEST_INSERTION S100 AC10 6 1	[0/-1]hard /[-8537205609.0]soft	[0/-1]hard /[-8537205609.0]soft	0.0E0/0.0E0 /0.0E0		

# Takeaways

- **Kogito** makes **Business Automation** working well in cloud environment
- **TrustyAI** adds value-added services to Kogito to enable **tracing, explainability** and **monitoring**
- **Explainability** is needed to **establish trust** in automated business processes
- **Counterfactual explanations** provide examples to explain how to obtain the **desired result**
- **OptaPlanner** is a really **powerful** and **flexible** constraint solver
- **OptaPlanner** can be used to **score a prediction**
- It is possible to do **optimization** on **top of predictions** to explain/enrich them

# Resources

- **Kogito** - <http://kogito.kie.org/>
- **TrustyAI** introduction: <https://blog.kie.org/2020/06/trusty-ai-introduction.html>
- **TrustyAI** aspects: <https://blog.kie.org/2020/06/trusty-ai-aspects.html>
- **Demo code**: <https://github.com/kiegroup/trusty-ai-sandbox/tree/master/counterfactual-op>
- **Example-Based Explanations**: <https://christophm.github.io/interpretable-ml-book/example-based.html>

# Thank you

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