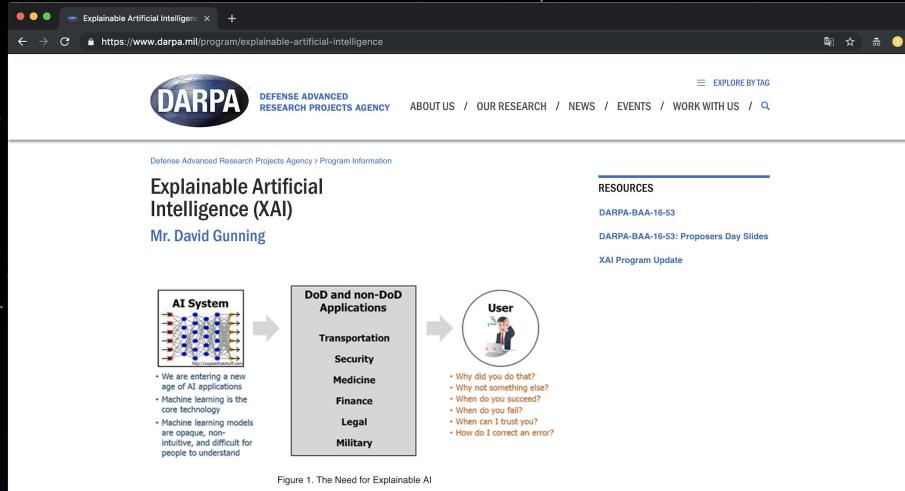


The 3 stages of

# XAI

How explainability facilitates real world deployment of AI



The current generation of AI systems offer tremendous benefits, but **their effectiveness will be limited by the machine's inability to explain its decisions and actions to users**

- David Gunning - DARPA/I2O XAI Program Update November 2017

# Intelligence Artificielle

Les défis actuels et l'action d'Inria



Inria

| LIVRE BLANC

| N°01

Les systèmes d'IA ont vocation à interagir avec des utilisateurs humains : **ils doivent donc être capables d'expliquer leur comportement**, de justifier d'une certaine manière les décisions qu'ils prennent afin que les utilisateurs humains puissent comprendre leurs actions et leurs motivations.

- *Intelligence Artificielle. Les défis actuels et l'action d'Inria*



## PREPARING FOR THE FUTURE OF ARTIFICIAL INTELLIGENCE

Executive Office of the President  
National Science and Technology Council  
Committee on Technology

October 2016



Federal agencies [...] should [...] ensure that AI-based products or services purchased with Federal grant funds **produce results in a sufficiently transparent fashion** and are supported by evidence of efficacy and fairness.

- *Preparing for the future of Artificial Intelligence*

# CÉDRIC VILLANI

Mathématicien et député de l'Essonne

## DONNER UN SENS À L'INTELLIGENCE ARTIFICIELLE

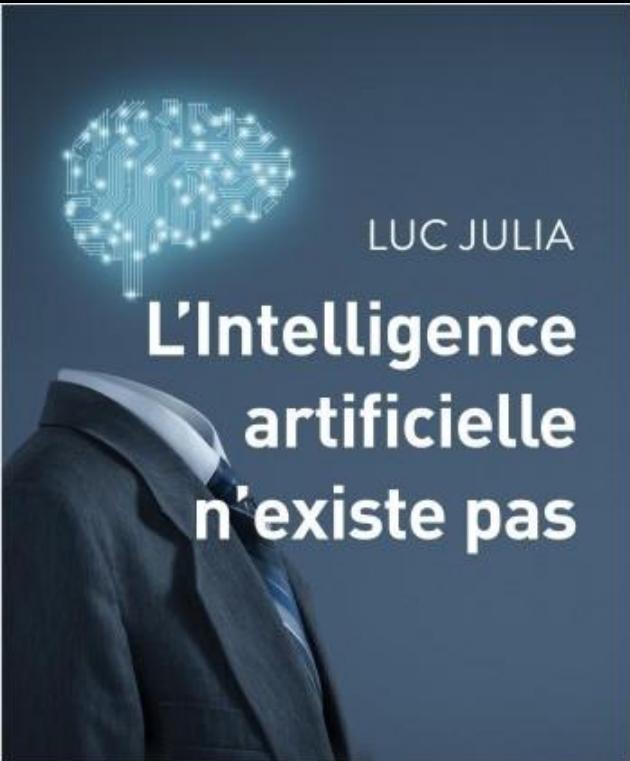
POUR UNE STRATÉGIE  
NATIONALE ET EUROPÉENNE

Composition de la mission

**Marc Schoenauer** Directeur de recherche INRIA • **Yann Bonnet** Secrétaire général du Conseil national du numérique • **Charly Berthet** Responsable juridique et institutionnel du Conseil national du numérique • **Anne-Charlotte Cornut** Rapporteur au Conseil national du numérique • **François Levin** Responsable des affaires économiques et sociales du Conseil national du numérique • **Bertrand Rondepierre** Ingénieur de l'armement, Direction générale de l'armement.

En premier lieu, il faut accroître la transparence et l'auditabilité des systèmes autonomes d'une part, en développant les capacités nécessaires pour observer, comprendre et auditer leur fonctionnement et, d'autre part, en **investissant massivement dans la recherche sur l'explicabilité.**

- [Cédric Villani - Donner Un Sens À L'Intelligence Artificielle](#)



Le cocréateur de *Siri*  
déconstruit le mythe de l'IA !

FIRST  
ÉDITIONS



L'explicabilité est importante parce qu'elle apporte la confiance. **Si on est capable d'expliquer pourquoi et comment on fait les choses, ça enlève le côté magique.**

- Luc Julia - L'intelligence artificielle n'existe pas

A screenshot of a web browser displaying a course page on Kaggle. The title is "Machine Learning Explainability". The sub-headline reads "Extract human understandable insights from any Machine Learning model". On the left, there's a sidebar titled "Your Progress" showing "Begin today!", "Overview", "Free", "4 hrs.", and "5 Lessons". A pink box at the bottom left says "Prerequisite Skills: Intro to Machine Learning". The main content area is titled "Lessons" and shows three sections: "1 Use Cases for Model Insights" (Tutorial), "2 Permutation Importance" (Tutorial and Exercise), and "3 Partial Plots" (Tutorial and Exercise). Each section has a brief description and small circular icons.

Many important decisions are made by humans. For these decisions, **insights can be more valuable than predictions.**

In practice, **showing insights [...]**  
**will help build trust, even**  
**among people with little deep**  
**knowledge of data science.**

- *Dan Becker - Data Scientist, Instructor @ Kaggle*



**Explanations are mandatory**  
when AI empowers humans to  
perform complex tasks

- Antoine Buhl - XAI, a game changer for AI in production @ AI Night 2019

When it comes to create AI for  
critical systems, **trustability and**  
**certifiability** are mandatory.

- David Sadek - XAI, a game changer for AI in production @ AI Night 2019

 IJCAI 2019 Workshop on Explainable Artifi...

# IJCAI 2019 WORKSHOP ON EXPLAINABLE ARTIFICIAL INTELLIGENCE (XAI)

11 August, 2019. Macau, China

<https://www.ijcai19.org/>



ⓘ

Quantmetry

Nos offres Nos compétences R&D et Innovation Qui sommes-nous ? Carrières Événements Blog

## Interprétabilité des modèles

De nombreux projets data s'appuient sur la création d'un algorithme dont les performances peuvent être correctes mais dont la mise en production pose question faute de fonctionnement compréhensible. Chez Quantmetry, nous sommes convaincus que cette démarche d'intelligibilité, nécessaire pour rendre moins opaque les modèles prédictifs, sera bientôt incontournable pour l'adoption de l'Intelligence Artificielle à grande échelle.

En nous appuyant sur des travaux de R&D internes, nos contributions open source et des échanges réguliers avec le monde de la recherche, nous avons développé une expertise, des convictions et un ensemble de bonnes pratiques sur l'utilisation de techniques favorisant l'interprétation des décisions prises par les modèles prédictifs.

visant à mieux comprendre les facteurs liés à une décision en particulier, nous sommes convaincus que notre expertise pourra vous être utile, comme elle l'a déjà été pour plusieurs de nos clients :

- Extraction de règles logiques pour décrire – et donc mieux comprendre – d'une manière approchée un modèle prédictif complexe.
- Activation des bons leviers d'action au niveau individuel, basé sur le calcul des variables contribuant le plus à une prédiction de churn associé.
- Analyse de l'impact de plusieurs variables issues de données externes, afin de valider que cet impact sur les prédictions était conforme à l'attendu (sens de variation, effet de seuils, etc.).

Vous pouvez retrouver notre livre blanc "IA, explique-toi !" qui instruit cette problématique de l'intelligibilité des modèles de machine



IA Explique-toi ! Quand la performance ne suffit pas

github.com

Why GitHub? Enterprise Explore Marketplace Pricing

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microsoft / interpret

Watch 95 Star 2,023 Fork 236

Code Issues 22 Pull requests 2 Projects 0 Security Insights

Branch: master interpret / README.md Find file Copy path

interpret-ml Move security section to SECURITY.MD from README.md 15ac82a 8 days ago

2 contributors

194 lines (140 sloc) | 6.54 KB Raw Blame History

# InterpretML - Alpha Release

license MIT python 3.5 | 3.6 | 3.7 pypi v0.1.18 build passing coverage 95% maintained yes

In the beginning machines learned in darkness, and data scientists struggled in the void to explain them.

Let there be light.

github.com

Why GitHub? Enterprise Explore Marketplace Pricing

Search Sign in Sign up

IBM / AIX360 Watch 20 Star 365 Fork 57

Code Issues 6 Pull requests 1 Projects 0 Security Insights

Branch: master AIX360 / README.md Find file Copy path

vijay-arya Merge pull request #31 from sadhamanus/master f26db44 on 16 Sep

5 contributors

140 lines (92 sloc) | 6.61 KB Raw Blame History

# AI Explainability 360 (v0.1.0)

build passing docs passing pypi package 0.1.0

The AI Explainability 360 toolkit is an open-source library that supports interpretability and explainability of datasets and machine learning models. The AI Explainability 360 Python package includes a comprehensive set of algorithms that cover different dimensions of explanations along with proxy explainability metrics.

The [AI Explainability 360 interactive experience](#) provides a gentle introduction to the concepts and capabilities by walking through an example use case for different consumer personas. The [tutorials and example notebooks](#) offer a

Technology   Use Cases   Pricing   Doc   API   About   Blog

# Explainable AI, as-a-service

API enabling product & operational teams to quickly deploy and run explainable AIs. craft ai decodes your data streams to deliver self learning services.

[Get in touch!](#) [Subscribe Newsletter](#)

The image shows three mobile device screens side-by-side, each displaying a different AI application interface. The first screen on the left shows the Direct Energie app with its logo and a teal speech bubble icon. The middle screen shows the Dalkia app with its logo and several teal horizontal bars. The third screen on the right shows the Mairie de Paris app with its logo and a teal speech bubble icon. In the bottom right corner of the dark blue background, there is a small white speech bubble icon.

How XAI makes a  
difference?

# What's an explanation?

Tim Miller - Explanation in Artificial Intelligence: Insights from the Social Sciences

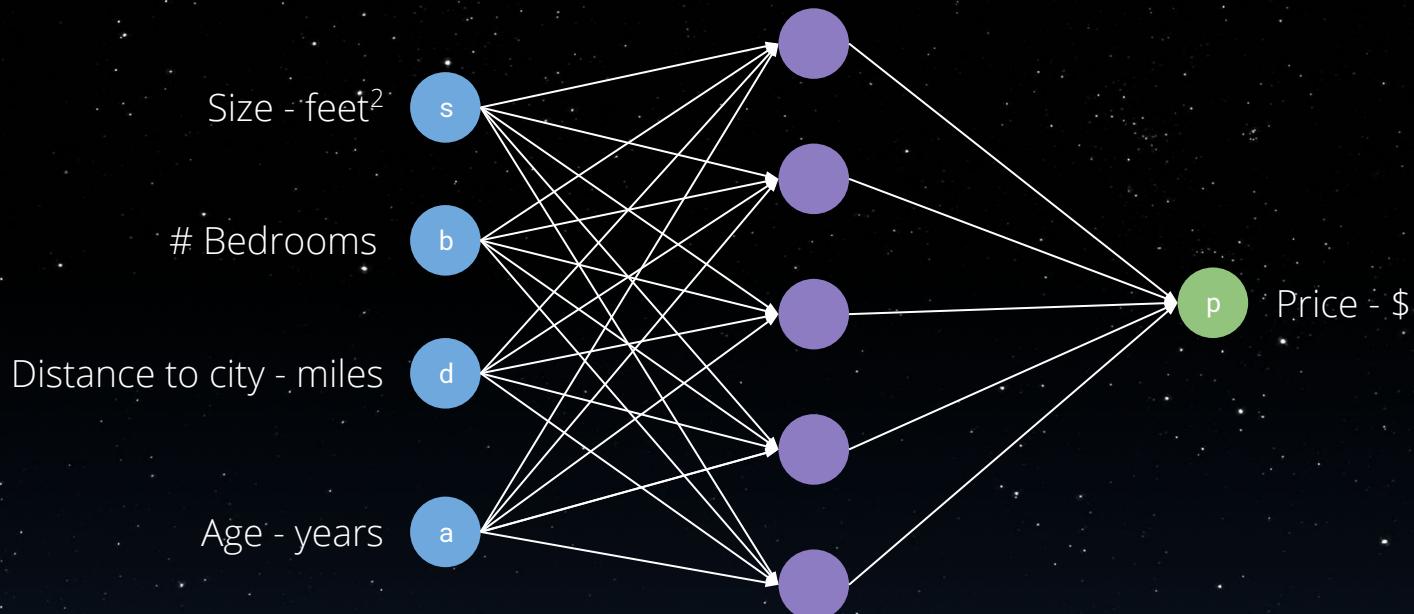
People look for explanations to improve their understanding of someone or something so that they can derive stable model that can be used for prediction and control

- Fritz Heider, Australian psychologist

1. Answer to "Why?" questions
2. Answer with contrastive explanations
3. Biased towards the explainee

# Non-explainable AI != Non-deterministic AI

[SuperDataScience - Artificial Neural Networks - How do Neural Networks Work?](#)

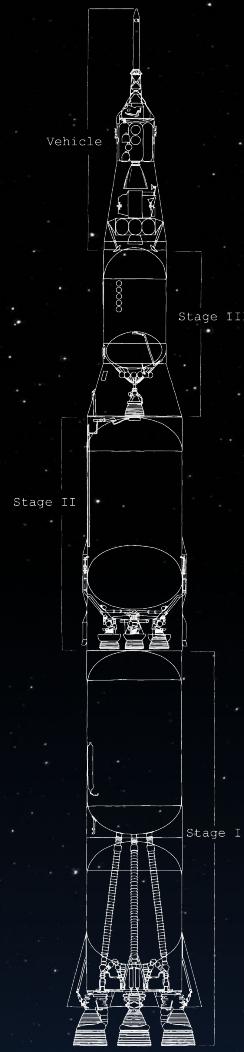


$$p = f(w_1 f(w_{11}s + w_{21}b + w_{31}d + w_{41}a) + w_2 f(w_{12}s + w_{22}b + w_{32}d + w_{42}a) + \dots)$$

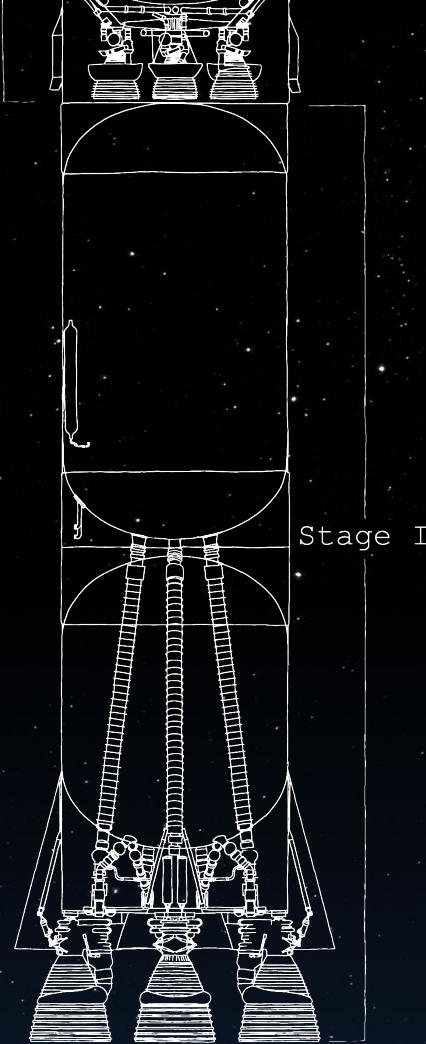
# Non-explainable AI != Non-deterministic AI

Alexey Kurakin, Ian Goodfellow, Samy Bengio - Adversarial examples in the physical world





# The 3 stages of XAI

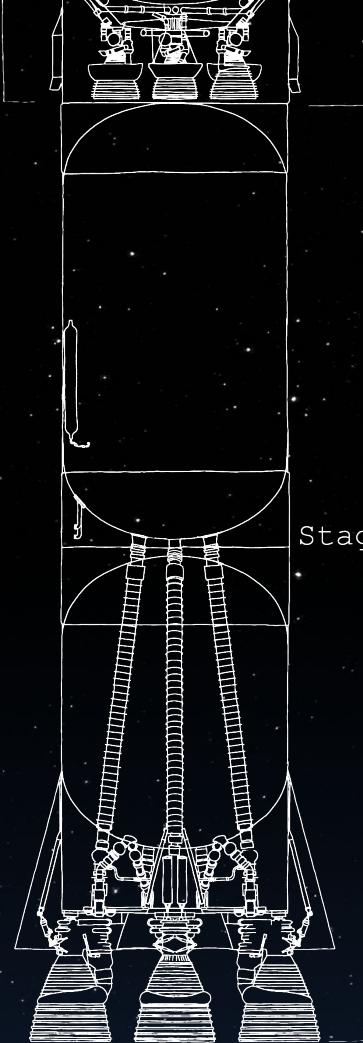


## Stage I

# Explainable building process

# Involve Business Experts

# Acceptability + Performances



Stage I  
**Some tools**

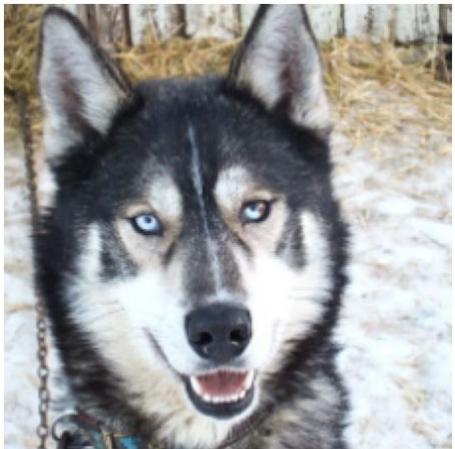
Visualization  
Simulation  
Offline debugging tools  
+ *upper stages tools*

Stage I

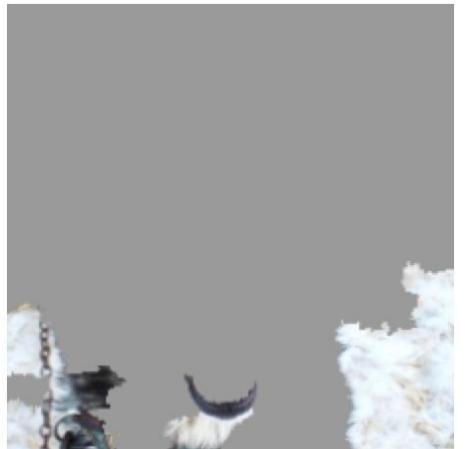
# Saliency Maps

[Ribeiro, M. T., S. Singh, et C. Guestrin (2016)]

Visualize important  
regions of an image



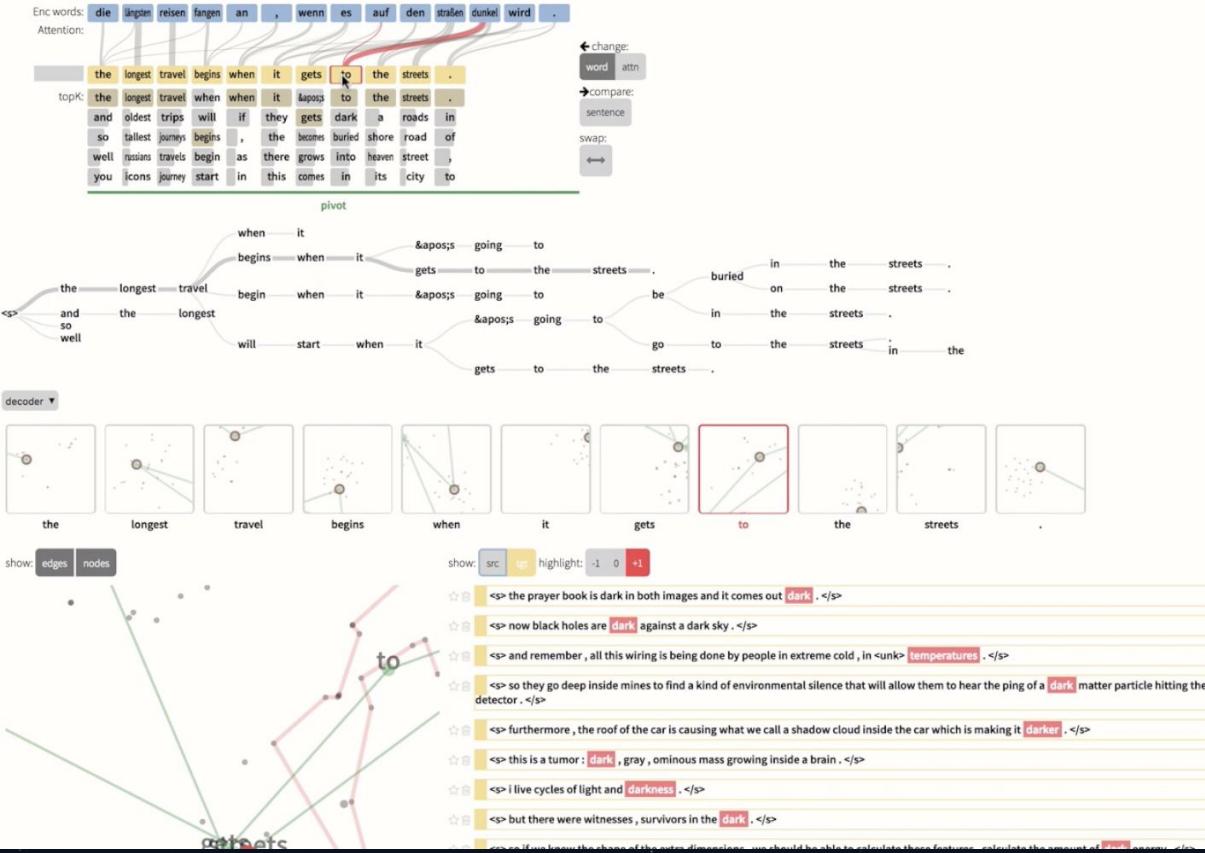
(a) Husky classified as wolf



(b) Explanation

Start entering some encoder sentence (enter triggers request)...

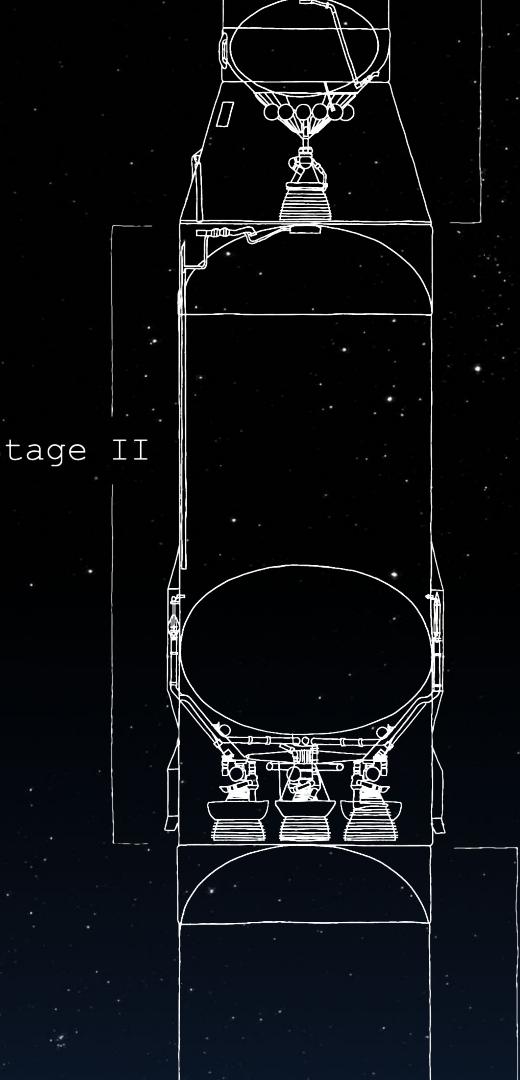
die längsten reisen fangen an , wenn es auf den sträßen dunkel wird .



# Stage I Seq2Seq-Vis

[Strobelt, H., S. Gehrmann, M. Behrisch, A. Perner, H. Pfister, et A. M. Rush (2018)]

# Translation system debugger & visualizer



Stage II

Explainable decisions

Follow Least Surprise Principle

Trust + Traceability

Stage II



## Stage II Some tools

### Local explanation generation (TreeInterpreter, LIME, SHAP...)

[Saabas, A. (2014); Ribeiro, M. T., S. Singh, et C. Guestrin (2016a); Lundberg, S. M. et S.-I. Lee (2017)]

+ *upper stages tools*



## Stage II SHAP

[Scott M. Lundberg, Su-In Lee - A Unified Approach to Interpreting Model Predictions - NeurIPS 2017]

Stage II

1. Select business understandable features  
 $x' = simpl\_feat(x)$

2. Fit a explainable model approximating the actual model

$$pred\_model(x) \approx expl\_model(x') = \phi_0 + \sum_{i=1}^{dim(x')} \phi_i x'_i$$



BLECKWEN

18/04/2019 - 07:28 | Alert creation: fraud suspicion

An alert has been created for suspicion of fraud.

#### RULES FEEDBACK

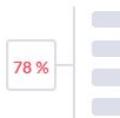
× ml

× RULE\_MODEL

MODEL\_SCORE > 0.5 => BLOCK

[See all rules](#)

#### MACHINE LEARNING FEEDBACK



- Debtor transfers count to creditor country
- Percentile amount debtor
- Debtor transfers count to creditor BIC
- Percentile amount debtor to creditor country

[See all the features](#)

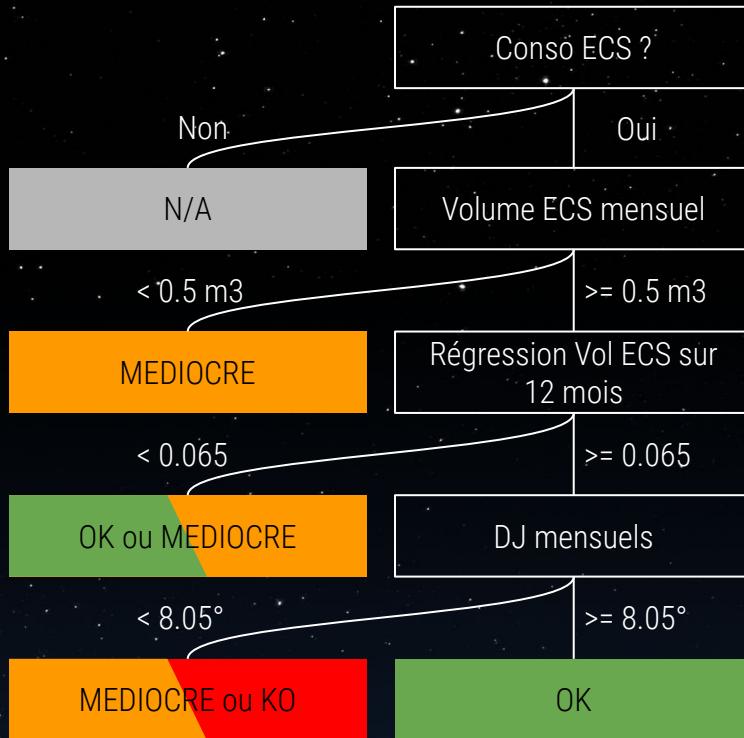
## Stage II Banking fraud detection

### Leveraging SHAP

**Explainability = Insights + Traceability**

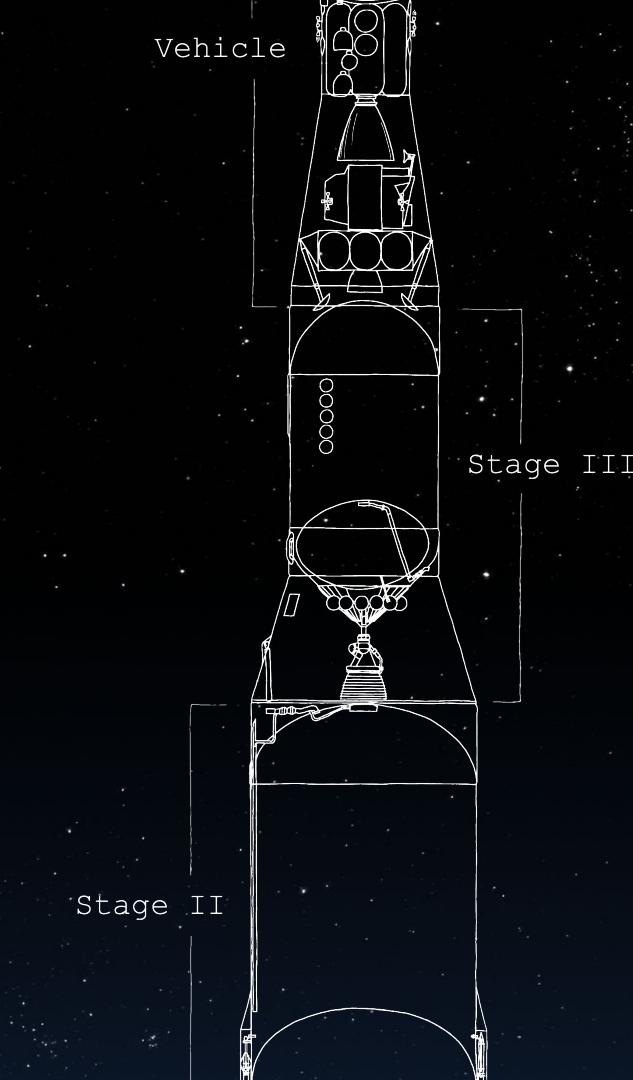
Stage II

## Energy manager assistant



Decision Tree to generate contrastive explanations

**Explainability = Productivity**



Vehicle

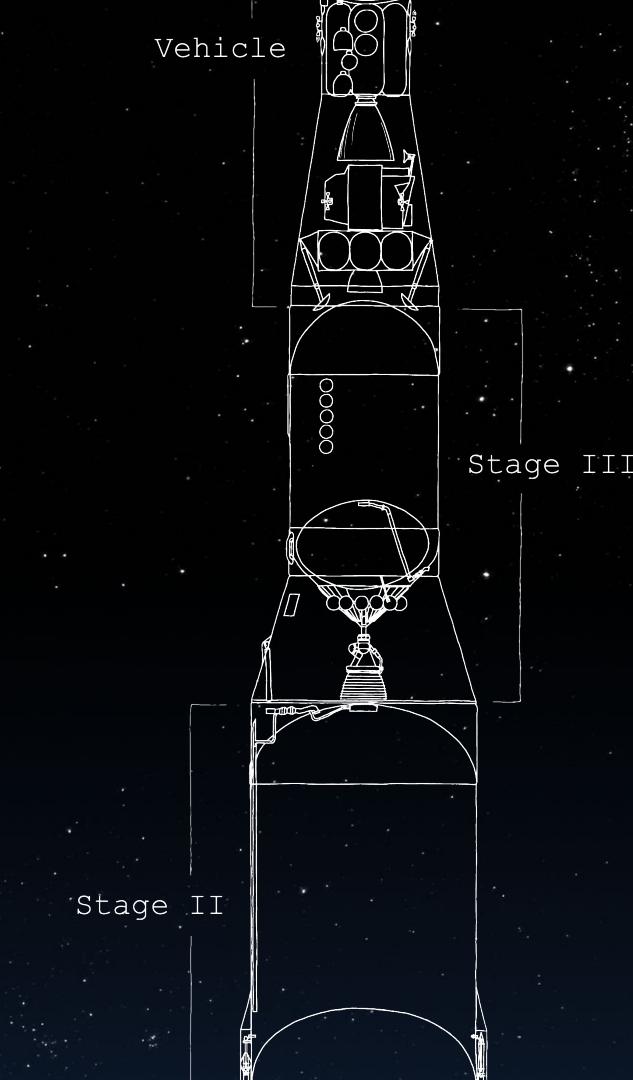
Stage III

## Explainable decision process

Enable interoperability with business logic

**Automation + Certifiability**

Stage II



Vehicle

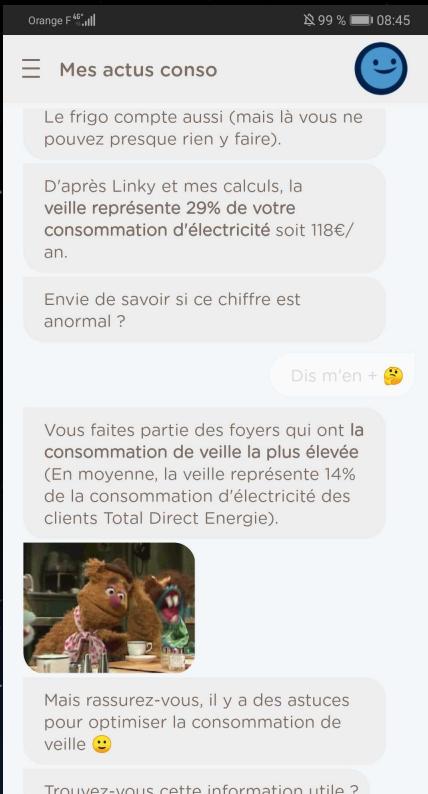
Stage III

Stage II

Stage III

## Some tools

Globally explainable models  
(Decision Trees, Business Rules,  
Regressions, ...)



Stage III

## Energy coach

Household consumption predictive model used as a knowledge base

**Explainability = Interface with symbolic systems**

# Challenges

Not because they are  
easy, but because they  
are hard

-John F. Kennedy

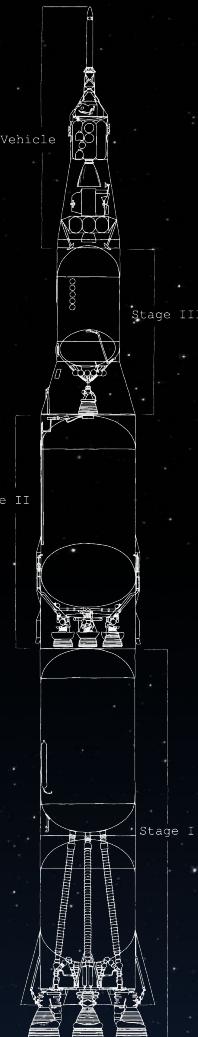
How can we evaluate explainability?

# Challenges

Not because they are  
easy, but because they  
are hard

-John F. Kennedy

Improve the performances of XAI  
Improve Data Engineering  
New Machine Learning approaches  
Hybrid models



## Stage III

# Explainable decision process

Enable interoperability with business logic

---

## Stage II

# Explainable decisions

Foster trusts with users & supervisors

---

## Stage I

# Explainable building process

Facilitate acceptance

# Takeaways

We set sail on this new sea because there is new knowledge to be gained, and new rights to be won, and they must be won and used for the progress of all people.

-John F. Kennedy

Explainability is an opportunity  
Regulation is coming

No system in production below stage II

