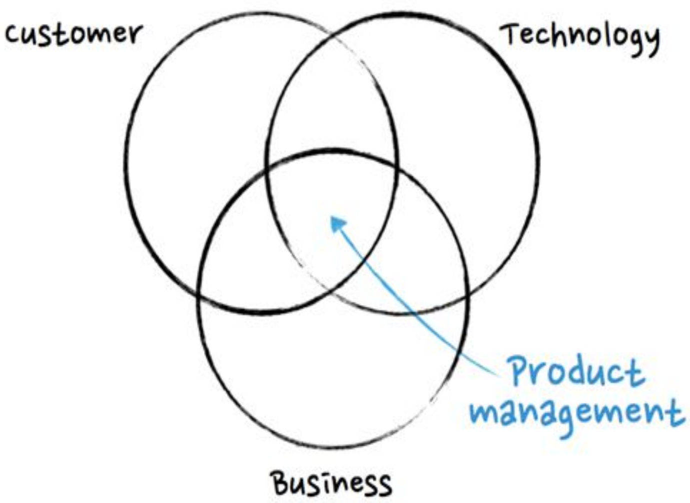
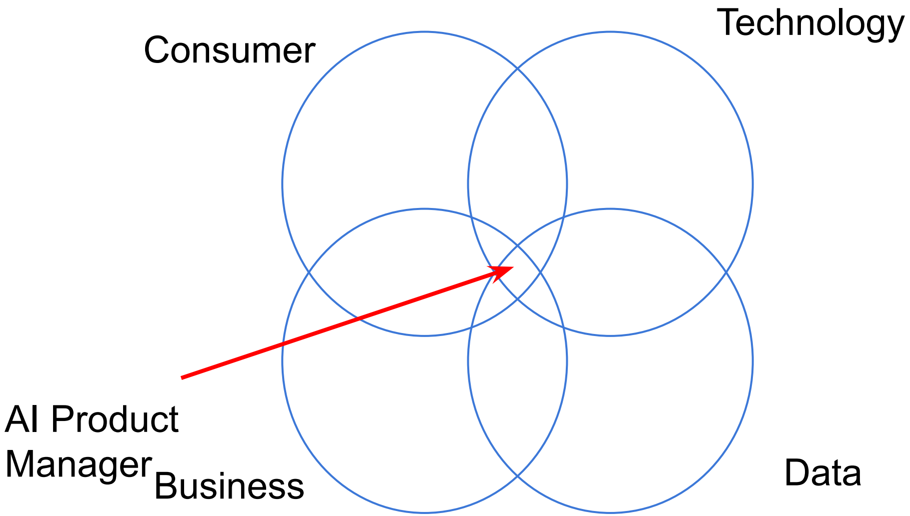
Components of Product Management in AI





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Role of a Product Manager in AI

You must be an **Analytics translator**

"Bridging the technical expertise of data engineers and data scientists with the operational expertise of marketing, supply chain, manufacturing, risk and other managers"

- HBR Definition

- Domain knowledge
- General technical skills
- Project management skills
- Entrepreneur mindset

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Role of a Product Manager in AI

You are going to spend a lot of time explaining **your role** AND **what is AI**

- Why we can do this?
- Why it is not ready yet?
- When will it be ready?
- Why I can’t have a roadmap?

And this is true for Product Management in general

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Role of a Product Manager in AI

As a Product Manager, you should care about security; and as a PM in AI there is also :

- Availability, Integrity and Confidentiality
- Collection, Security, Variety and Accuracy of Data
- Work on project to collect more data from consumers, enriching data with others sources of information, cleaning and rearranging data

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Product Management vs PM in AI

Going from a deterministic mindset to a probabilistic mindset
Identify business opportunity and leverage AI to answer it

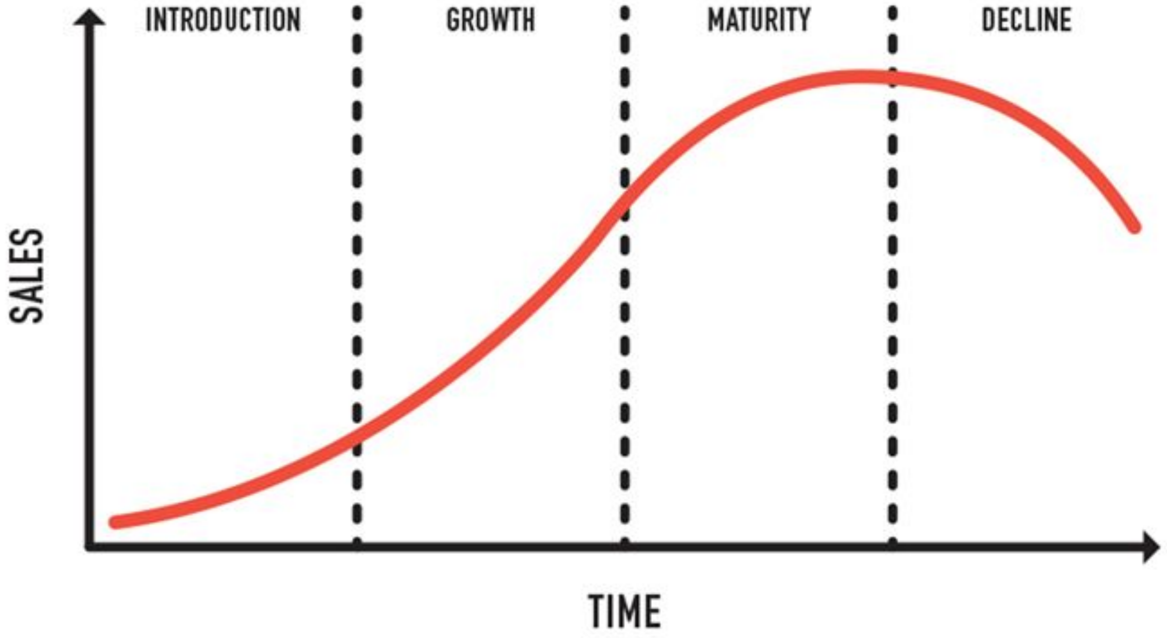
II. AI within the organization

1. Traditional product lifecycle

1. AI Hierarchy of needs

1. What about the Agile Process?

1. Traditional product lifecycle - Part 1



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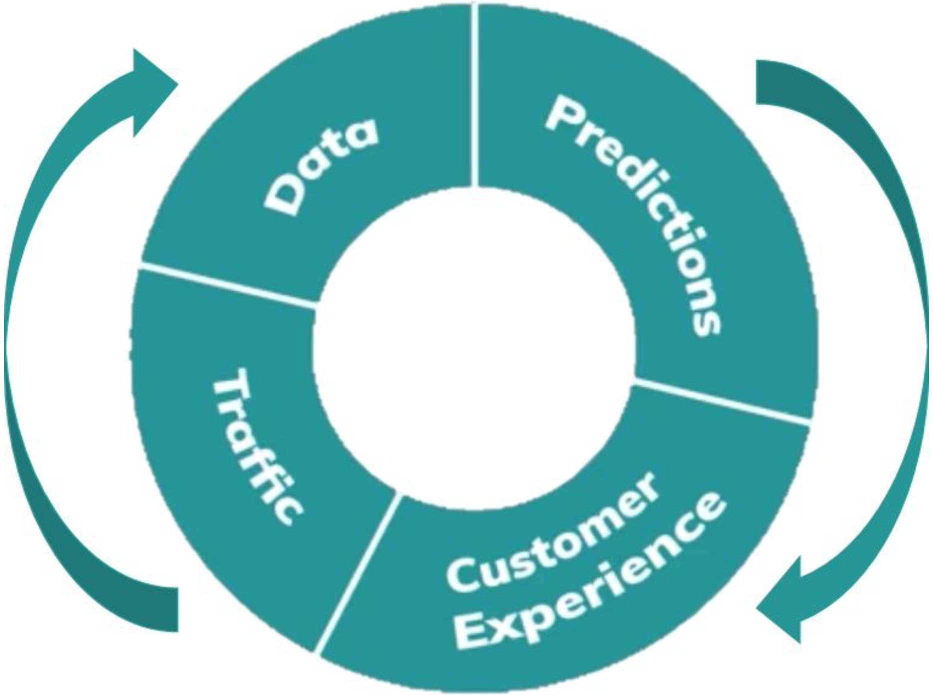
1. Traditional product lifecycle - Part 2



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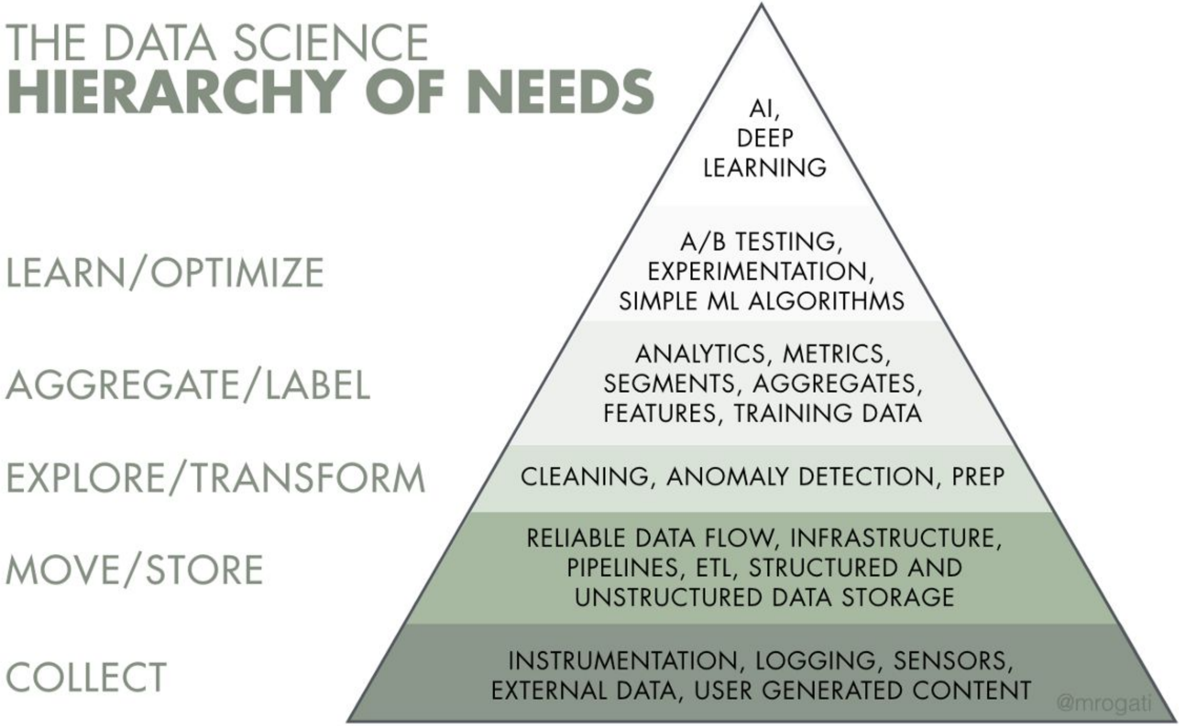
2. AI Hierarchy of needs



1. First step - Prototyping

What is a prototype?

- First version of the product or a model from which other iterations will be build on and developed

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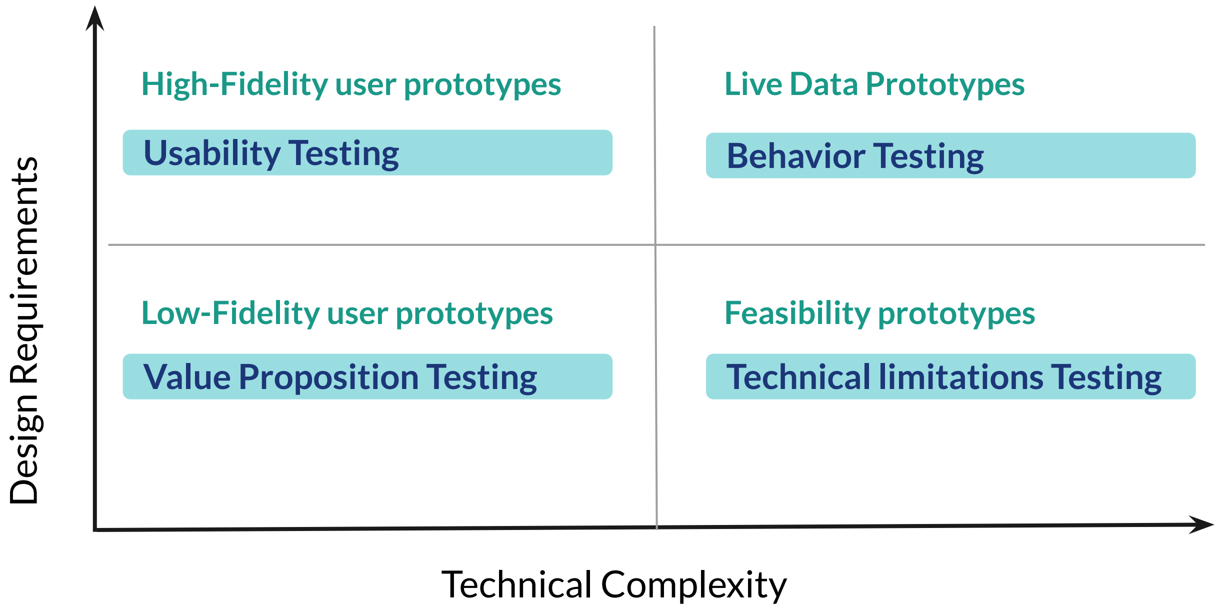
1. First step - Different types of prototypes



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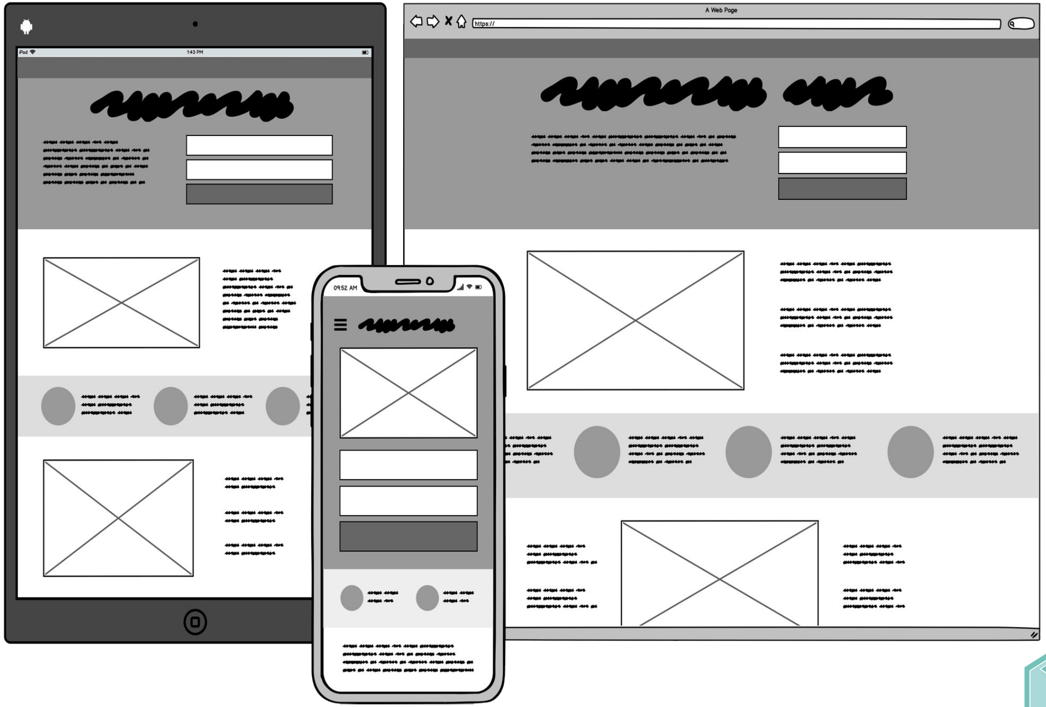
1. First step - Prototyping - Wireframes



1. First step - Prototyping - WoZ & Concierge

- **AI Personality Design Experiments**
  -> Find and build a persona that your user will respond positively

- **Wizard of Oz** -> Product that brings the value however it is operated by a human and the user thinks it's fully automated
  -> Good way to see how people react to it

- **Concierge Experiments (hotel experience)** -> Product that brings the value however it is operated by a human and the user knows about it
  -> The value is higher as users know they are interacting with a human

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2. Check up point - Ready for the second step?

Some considerations first :

- Are you sure AI is necessary to solve the problem?
- AI is seen as a magical recipe that will solve everything on its own
- It requires a lot of human power and your company needs to be ready to do the investment
- It is a commitment

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II. Machine Learning Canvas

1. Process to develop in house Machine Learning

1. Machine Learning Canvas

1. Process to develop in house Machine Learning

- ML systems takes into account data in a certain format to build models and predict the future
- From there the organization can act on the information received from the ML system to then mitigate the situation
- There is disconnect between the business' objectives of the organization and the people that build systems

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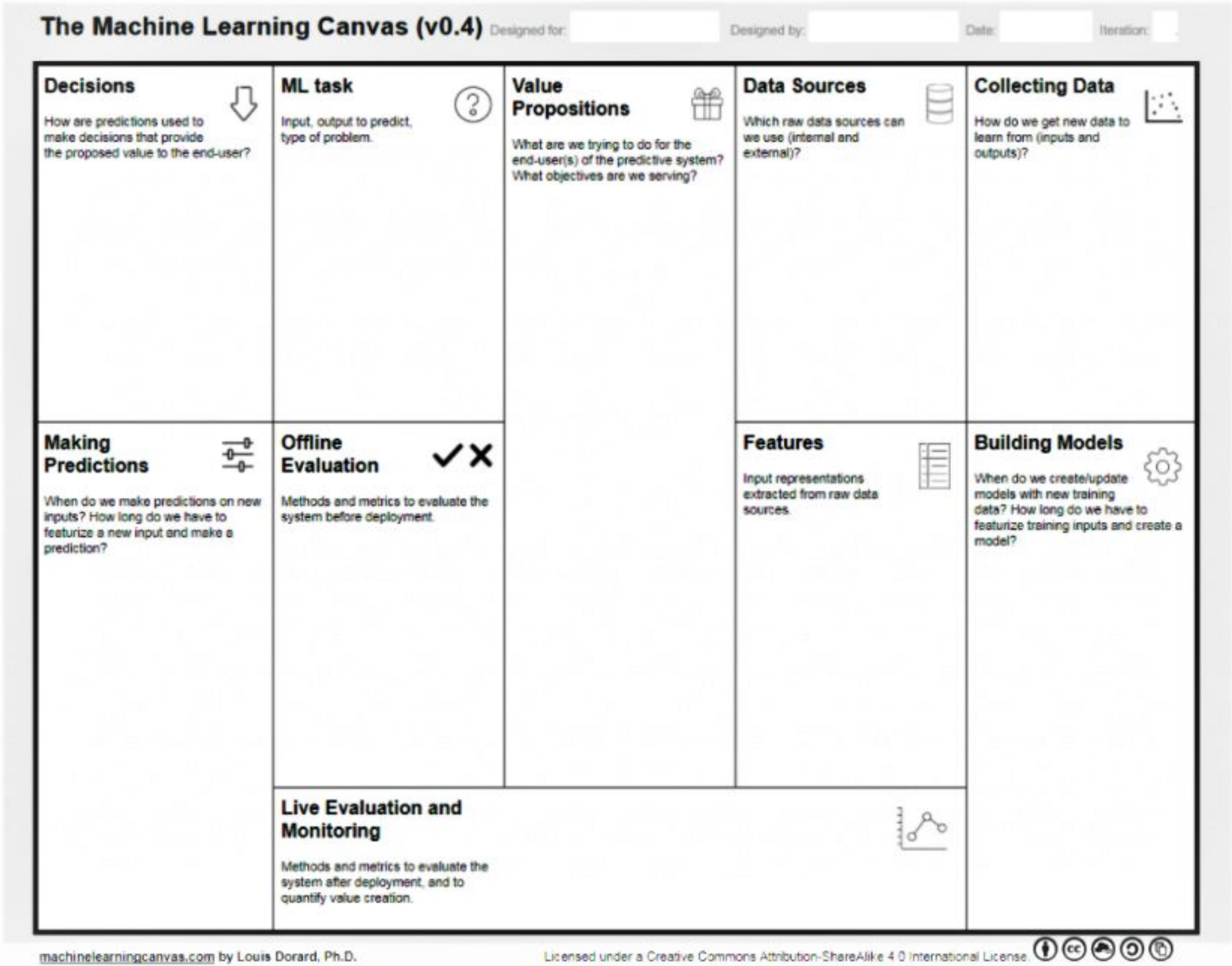

The Machine Learning Canvas (v0.4)

Designed for: | Designed by: | Date: | Iteration:

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How are predictions used to make decisions that provide the proposed value to the end-user?

ML task
Input, output to predict, type of problem.

Value Propositions
What are we trying to do for the end-user(s) of the predictive system? What objectives are we serving?

Data Sources
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Collecting Data
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Making Predictions
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Offline Evaluation
Methods and metrics to evaluate the system before deployment.

Features
Input representations extracted from raw data sources.

Building Models
When do we create/update models with new training data? How long do we have to featurize training inputs and create a model?

Live Evaluation and Monitoring
Methods and metrics to evaluate the system after deployment, and to quantify value creation.

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2. Machine Learning Canvas

- It's **a tool for visualising the learnings elements happening in the intelligent system**
- It consists of **interlinked key elements** from the value proposition, the learning elements to the predictions
- The **What + Why + Who and the How**

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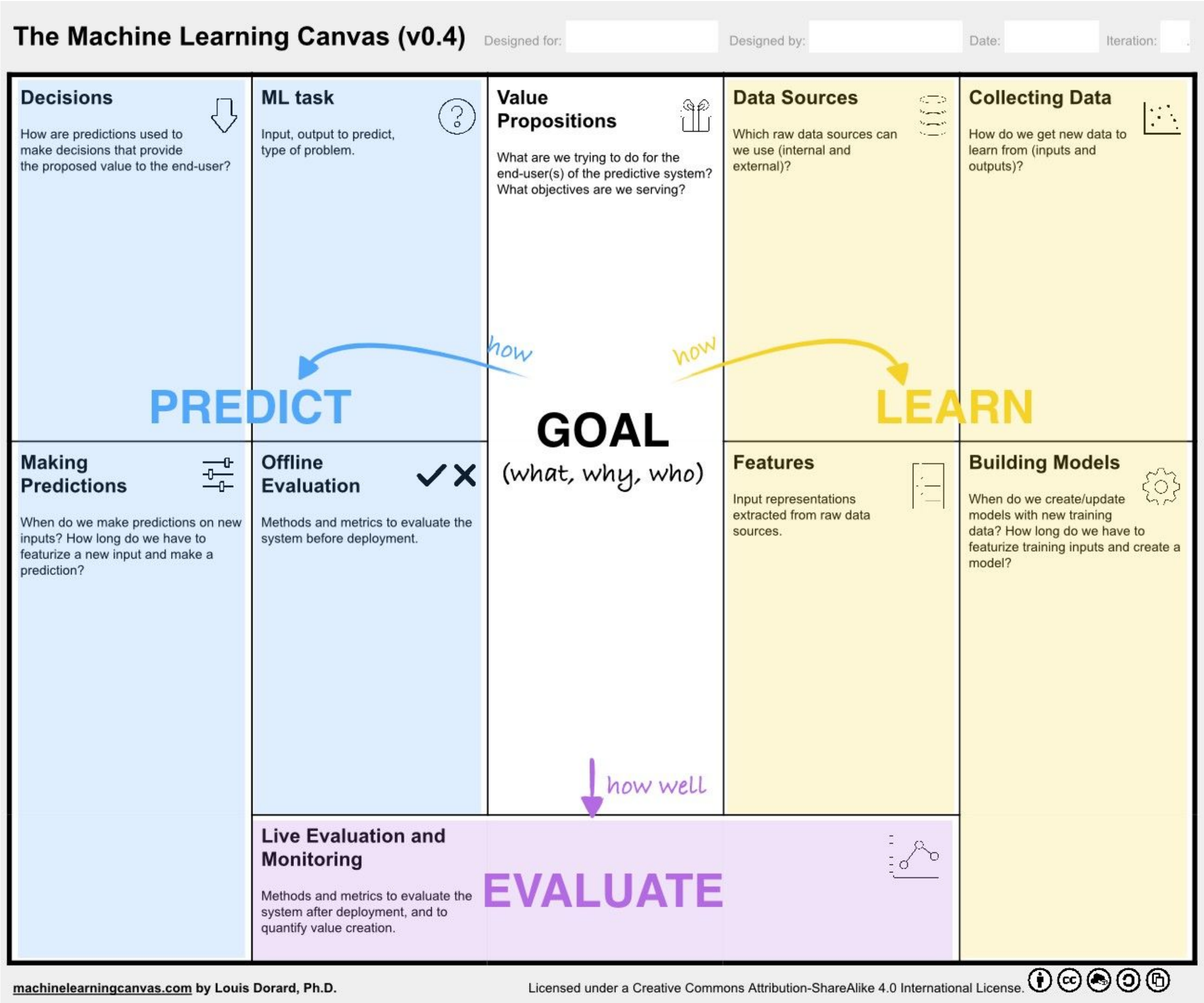
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2. Machine Learning Canvas - Difference with BM Canvas

Business Model

- Strategic Thinking
- Linking stakeholders with the product management and dev team
- What is the value proposition?
- Which consumers are we serving?
- How are we serving them?

Machine Learning

- Execution Thinking
- Linking with the team together: PM, Designer, Data Scientist, Data Engineers
- What data are we learning from?
- What kind of predictions we are making and how are we using them?
- A snapshot that can evolve through time

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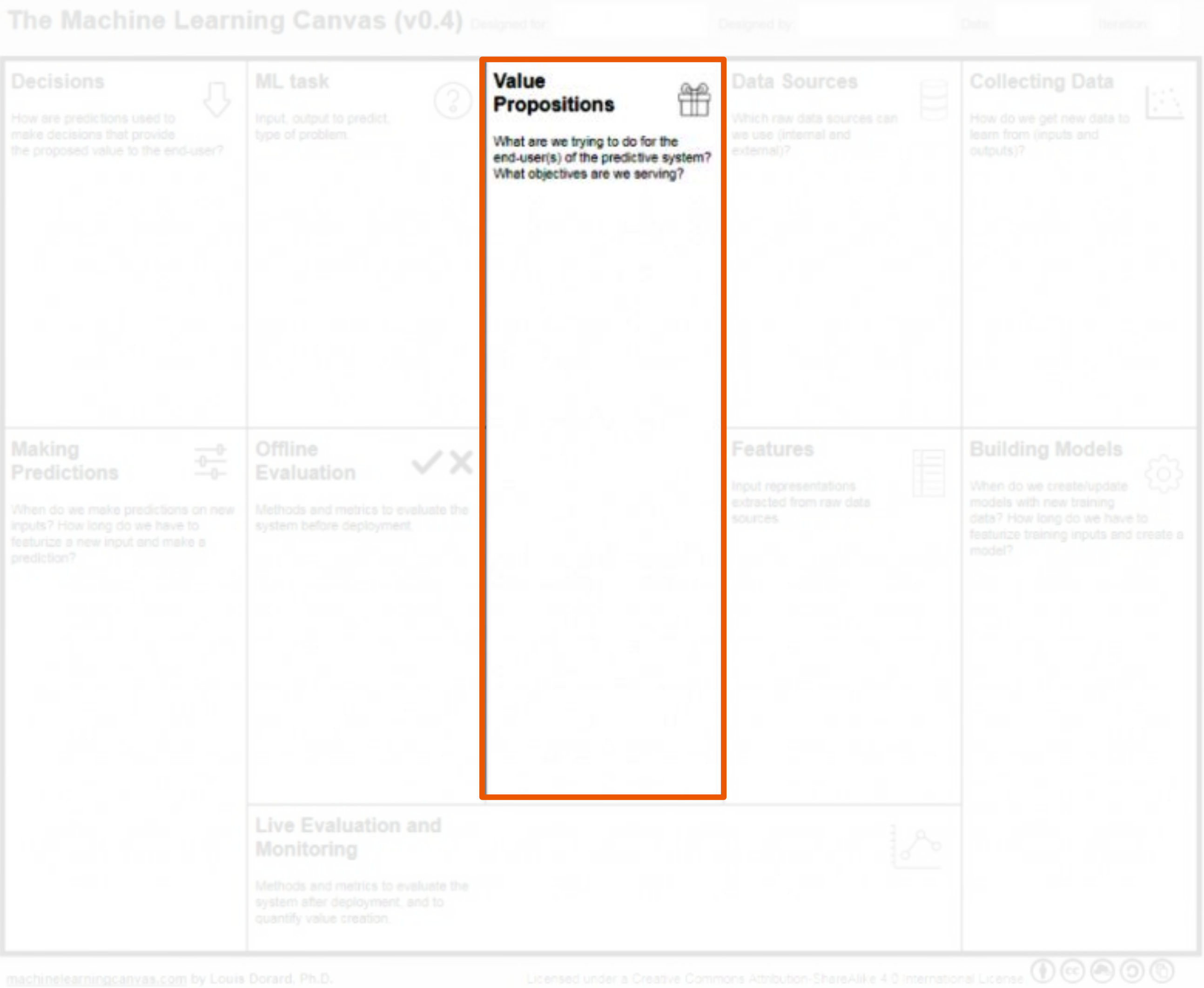
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2. Machine Learning Canvas - Value Propositions

- This is the central part of your Machine Learning System
- The Value proposition is the GOAL of your ML
- This is the What + Why + Who
- Use what you have learned from the Business Model, the personas and the testing you have done in the previous part

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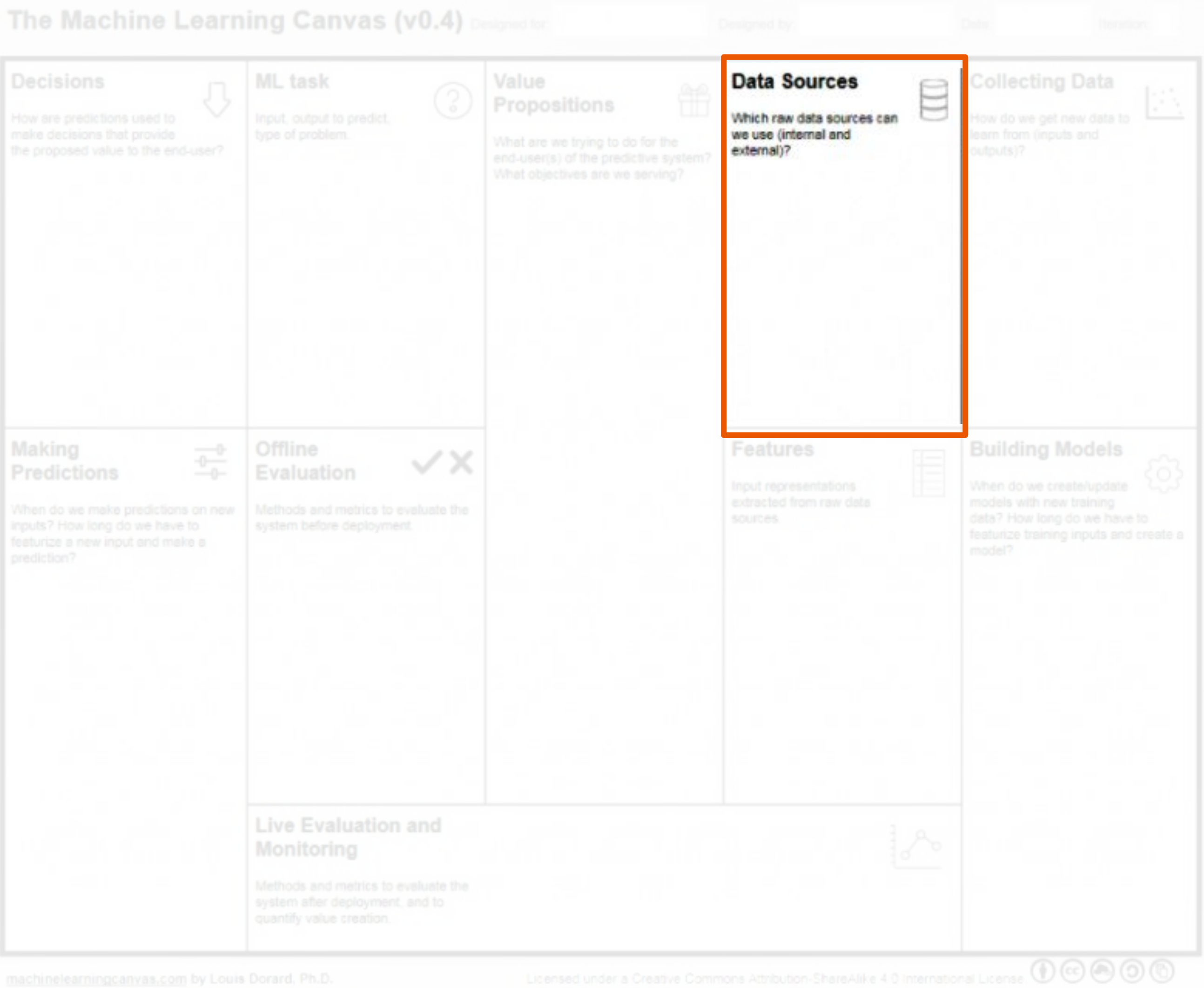
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2. Machine Learning Canvas - Data sources

- The data sources are the input for your ML Model
- Without enough data you are basically putting on pause every development until enough data is collected cleaned and processed
- This is why **you need a Data Strategy**

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2. Machine Learning Canvas - Data sources

- As a PM in AI you are responsible for the product and the vision and strategy around it; and as importantly you are ensuring that your team has enough data to build the AI and data product
- It means spending as much time on the product lifecycle as :
  - Negotiating contracts with external suppliers to acquire data
  - Working with your team creating new features for the product
  - Developing instructions on how to review and label the data

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2. Machine Learning Canvas - Data sources

- You need to think ahead
- Think about your assets and think about what makes you different from your competition
- What data will push you forward?
- What proprietary data your organisation posses that can’t be found elsewhere?

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2. Machine Learning Canvas - Data sources

You need to handle a part of the data strategy

Run the Business

- Process optimisation
- Managing data scientist workflow
- How data should be stored and processing be speed up

-> **Responsibility of Data leads**

Grow the Business

- Insight innovation
- Growing Revenues
- Exploring data

-> **Responsibility of the PM**

2. Machine Learning Canvas - Data sources

- Take back your SWOT analysis and focus on the Data side
- Focus on a strategy that improves the areas of data weaknesses
- Generally it will be :
    - Not having enough data
    - Lack of variety
    - Not having the right kind of data
    - Not labeled data

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2. Machine Learning Canvas - Data sources

5 ways to find Data :

1. Open Data
2. Company Data
3. Crowdsourcing label data
4. New Feature data
5. Acquired/Purchased data

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2. Machine Learning Canvas - Data sources

Method 1 : Open Data

- Open to everyone
- Available and easily accessible
- Can be reused and redistributed
- No restrictions on use

-> Pros - More data to train your model and easily accessible

-> Cons - Can you trust it or is it specific enough

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2. Machine Learning Canvas - Data sources

Method 2 : Company Data

- Easiest one as it is uniquely yours
- Faster to get for your team
- Unique competitive advantage

2. Machine Learning Canvas - Data sources

Method 3 : Crowdsourcing Label data

- Data may be missing labels that is needed to train your model
- As a PM and for your company you may have to set your own rules
- You may want to use an external company to do it

  1. Specialisation
  2. Cost
  3. Speed
  4. Training

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2. Machine Learning Canvas - Data sources

Method 4 : New Feature data

- How can you build in your experience a feature for data collection?
- Adding a new form
- A new functionality of a product will collect data on user behaviour

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2. Machine Learning Canvas - Data sources

Method 5 : Acquiring data

- Acquiring a company directly for their data
- Licensing the use of their data

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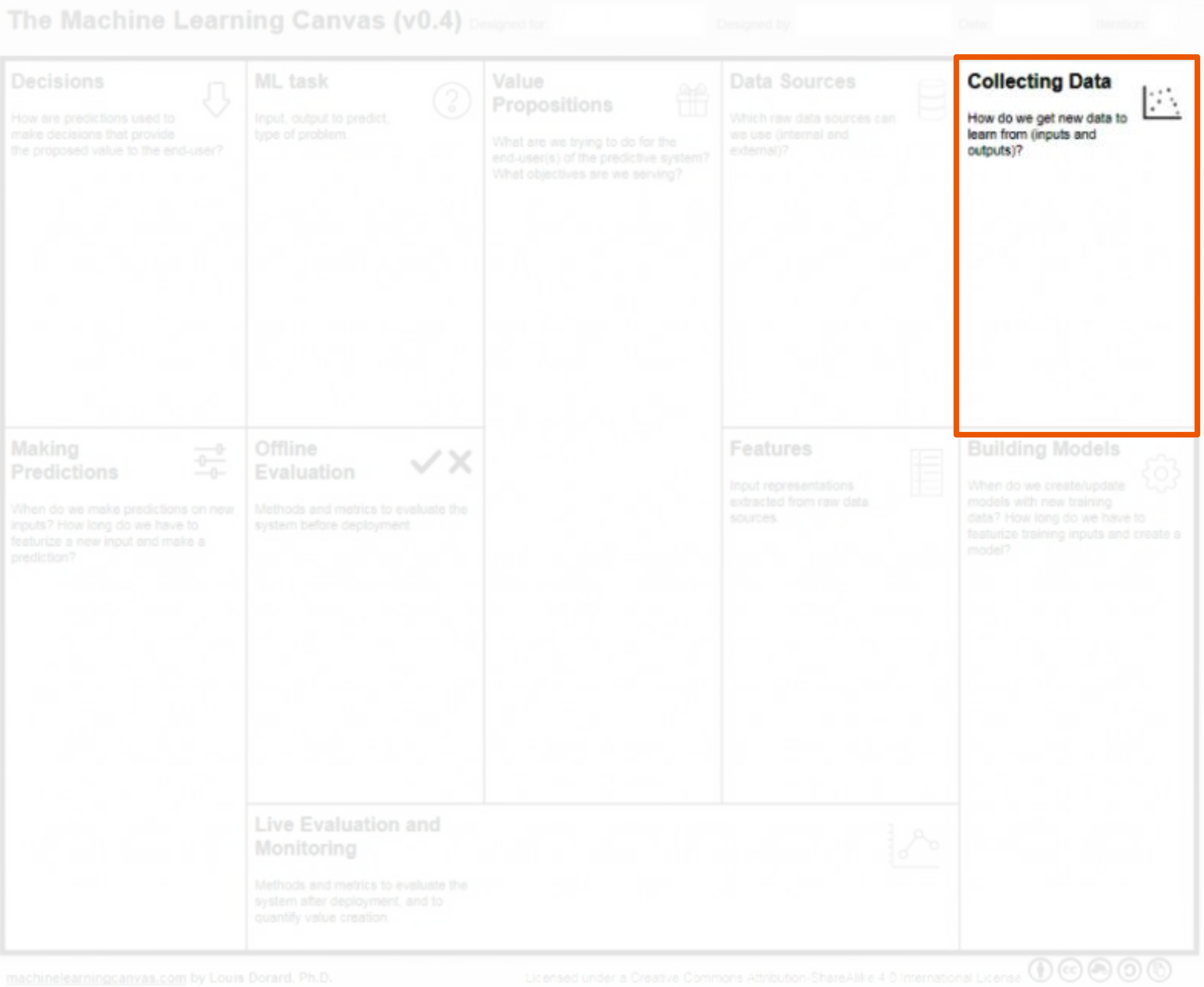
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2. Machine Learning Canvas - Collecting Data

- *How do we get new data to learn from?*
- Output data to learn from
- Data sources can be seen as input and the methods use can also work to find the output

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2. Machine Learning Canvas - Collecting Data

Different techniques

- Explicit Feedback
- Being smart and getting it implicitly
- Data augmentation or data generation
- Sometimes you need to wait

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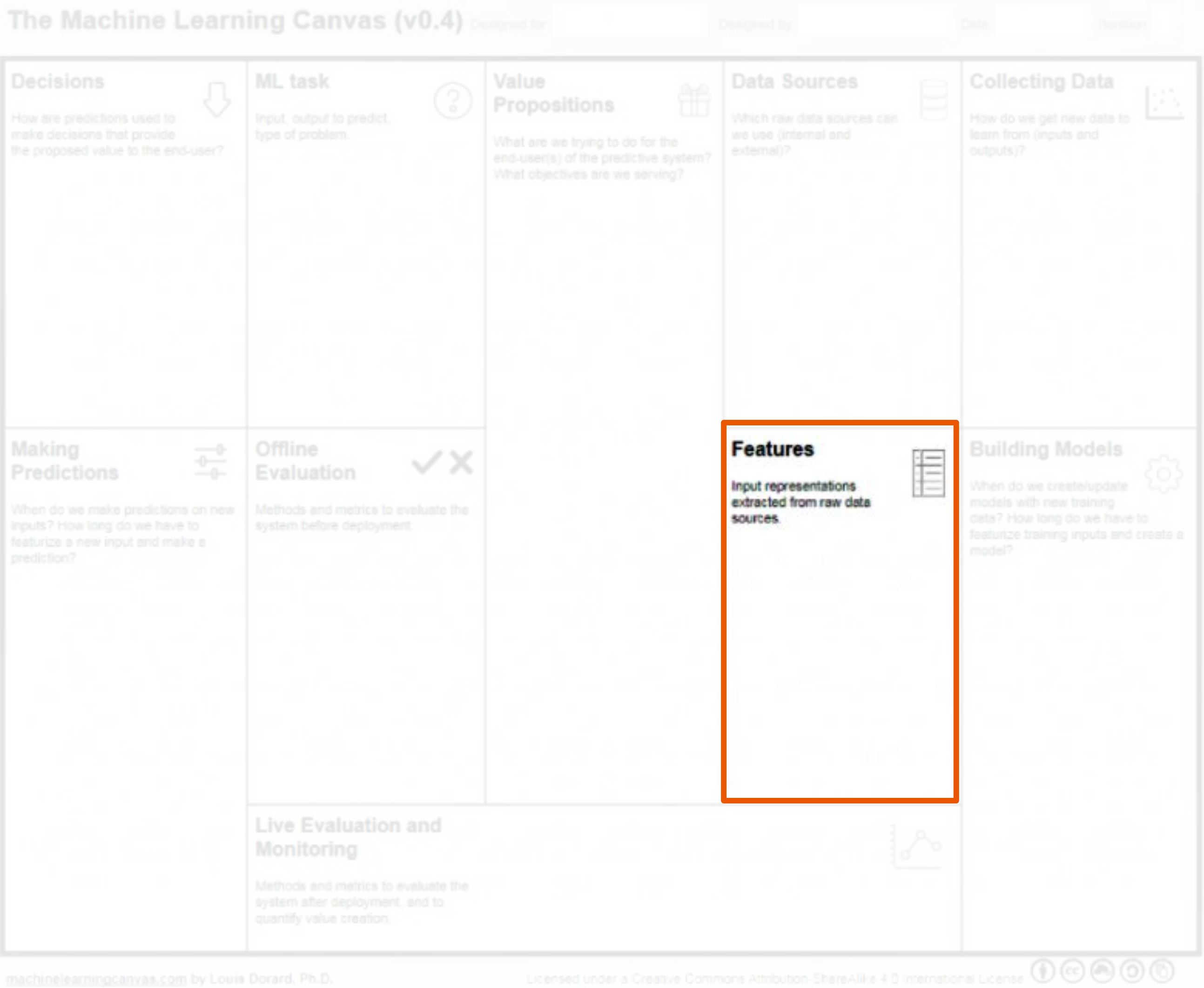
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2. Machine Learning Canvas - Features

Once you have the data, what do you do with it?

- Remember that your goal is to treat this data to predict an outcome on an object
- You need to have a computer representation whether it’s numerical, categorical or textual values
- If you think about spatial value, you need to think about a radius for example
- If you think about time sensitive values, you need to think about a period of time

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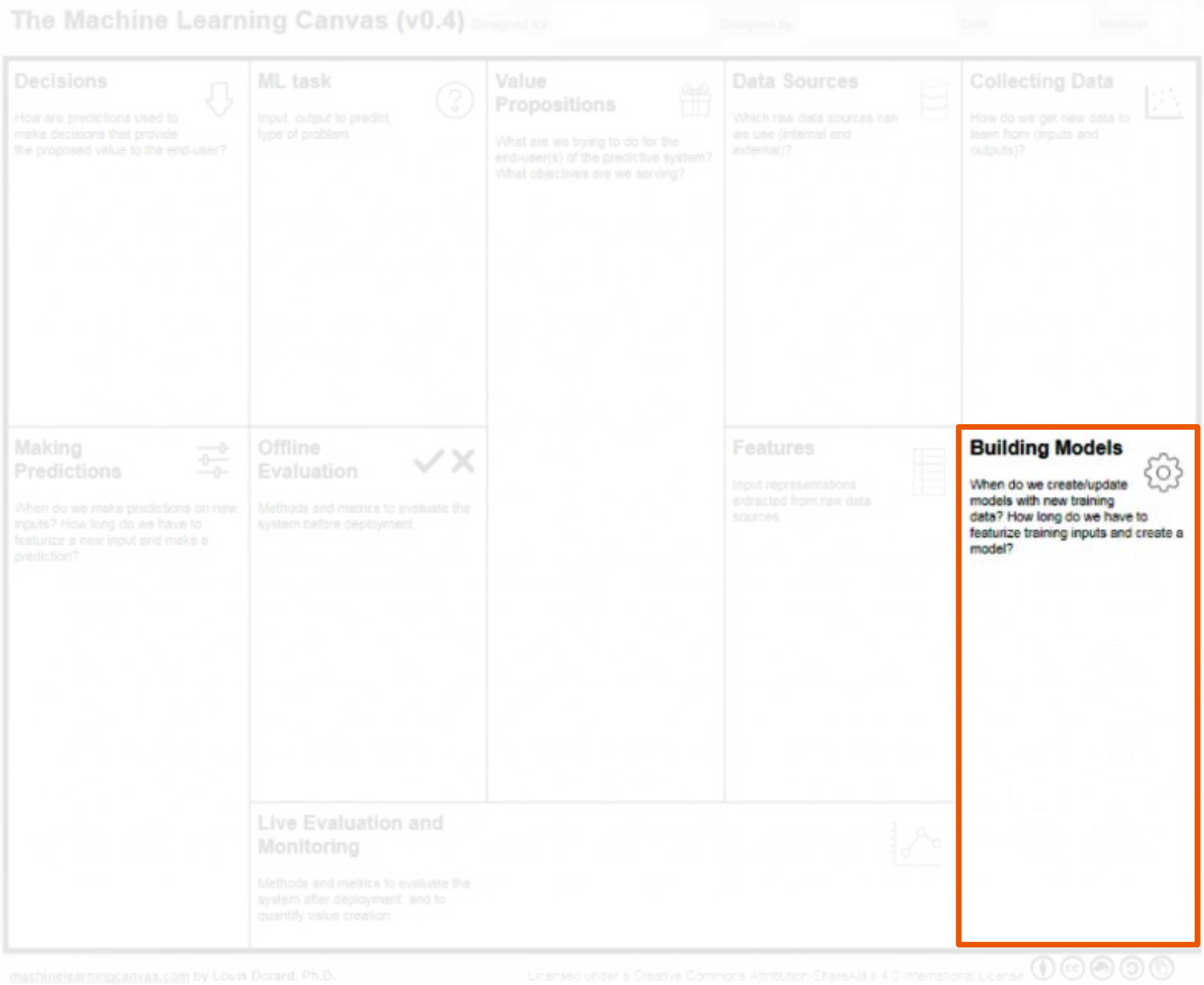
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2. Machine Learning Canvas - Building Models

- ML Model = Training Data + ML Learning Algorithm
- When building model, we have to think about when it’s useful to update the model and how much time can be allocated for it
- The domain generally dictate both of these components

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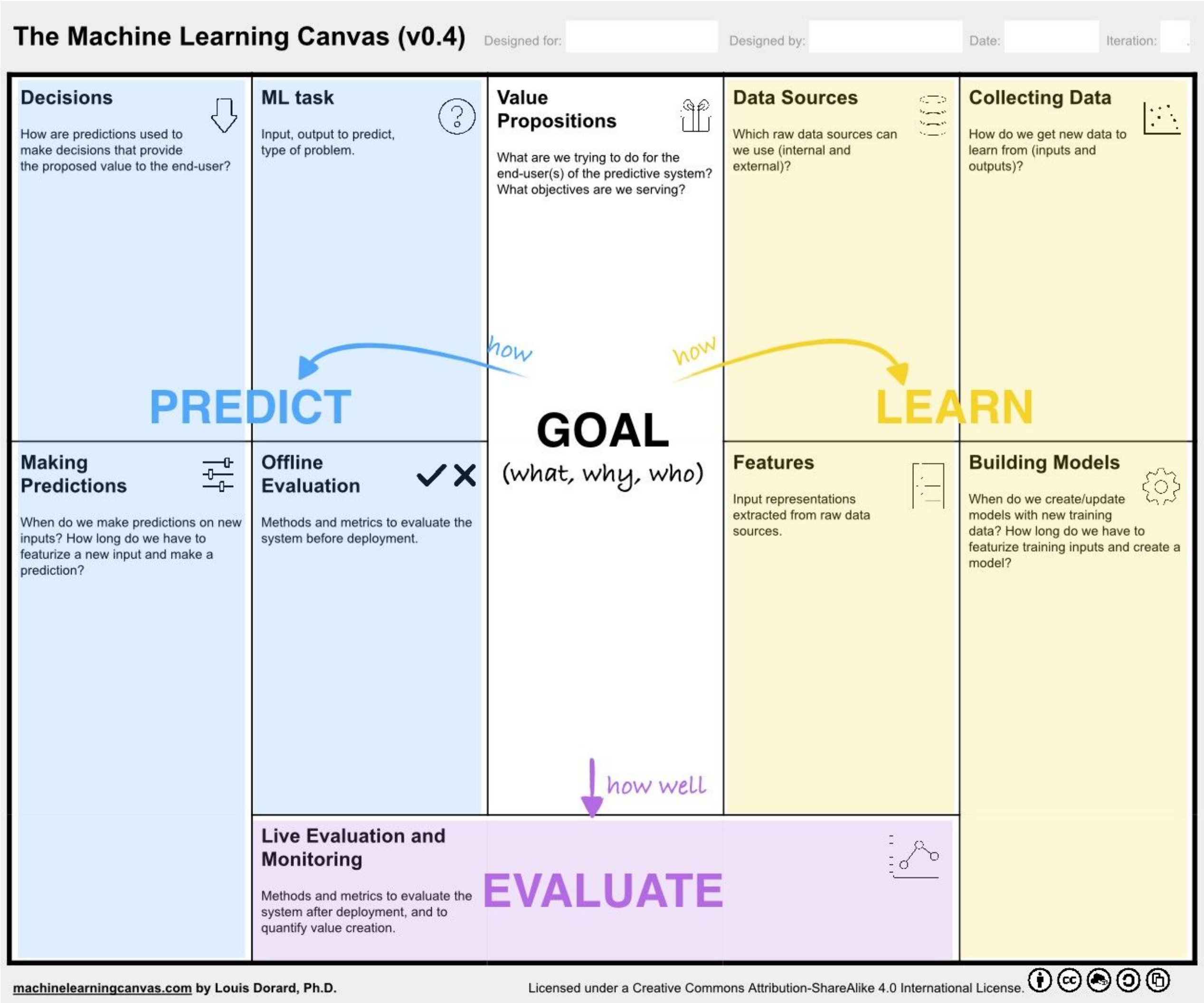
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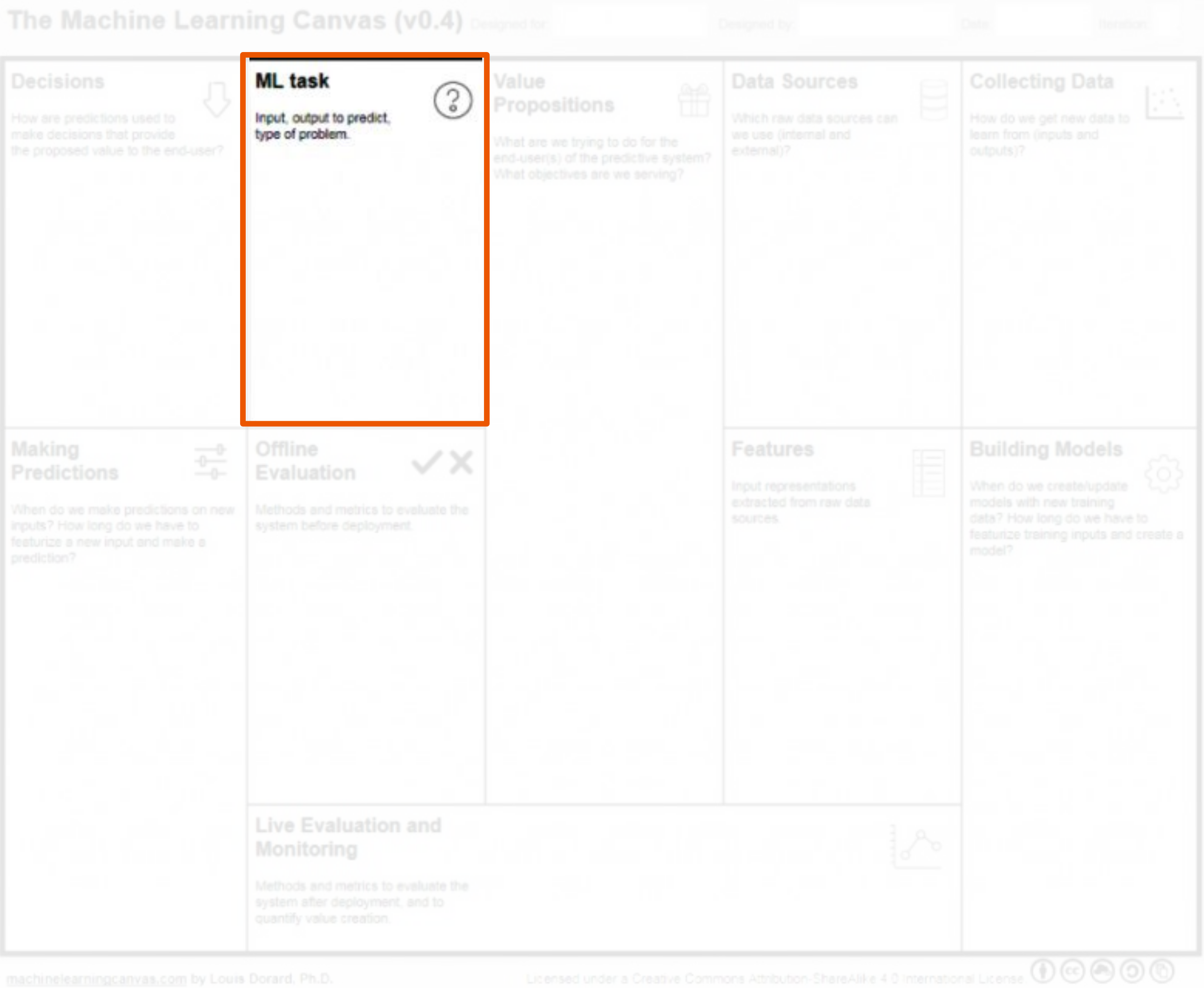
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2. Machine Learning Canvas - ML Task

What is the prediction task and how you will answer it?

Three aspects to the ML Task

- Input data
- Output Data
- Baseline - Give insights on data preparation for *Features* and on *Model Building* section

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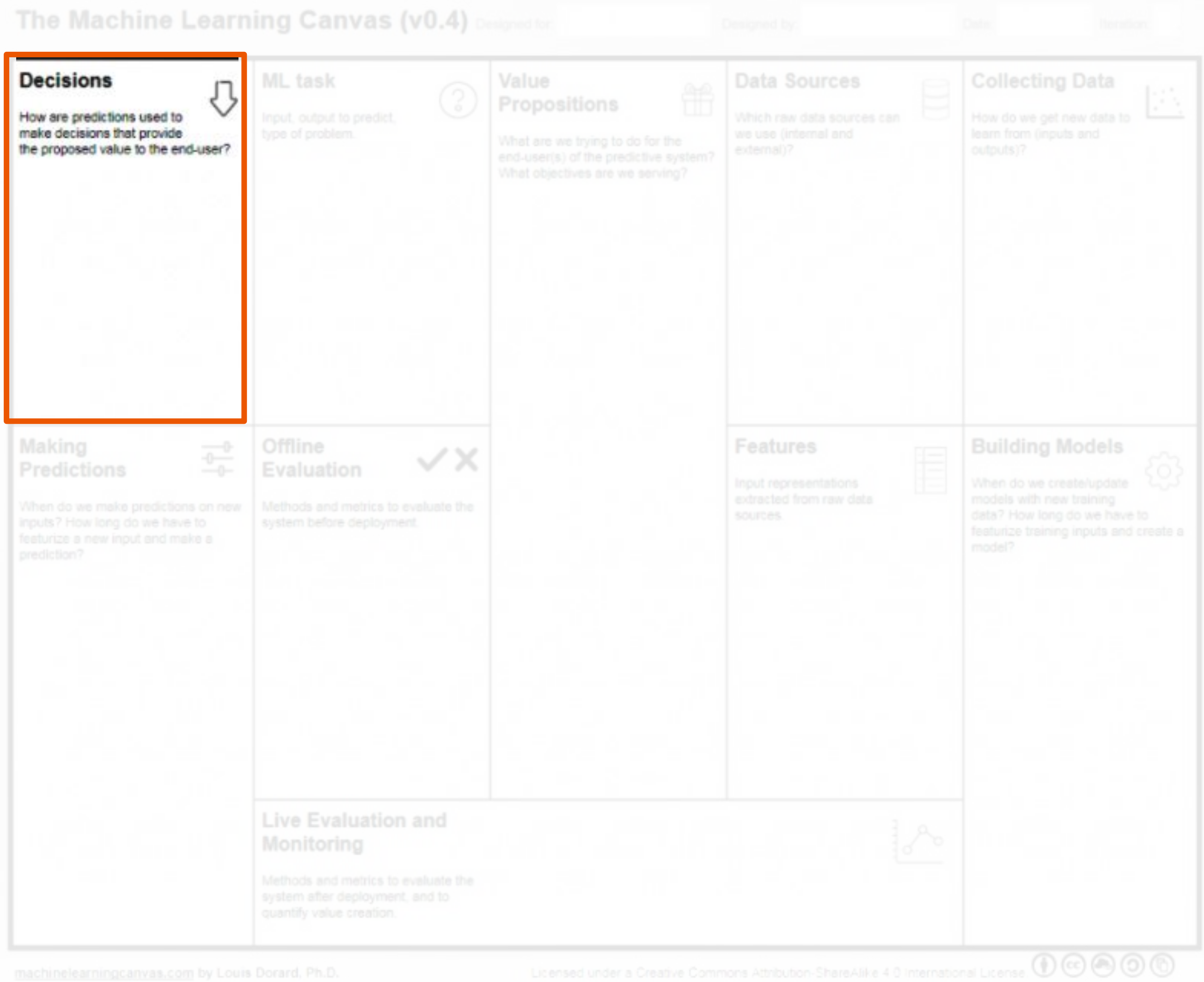
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2. Machine Learning Canvas - Decisions

When and how are predictions used to make decisions that provide the proposed value to the end-user?

- *Great predictive modeling is important, but as products become more sophisticated, it disappears into the plumbing. (Jeremy Howard)*

- Once you have done your prediction, the question is what to do with it and transform it into a concrete action?
  - When are you going to use those predictions?
  - How confident are you in the model to take decision?
  - Prescription or fully automated?

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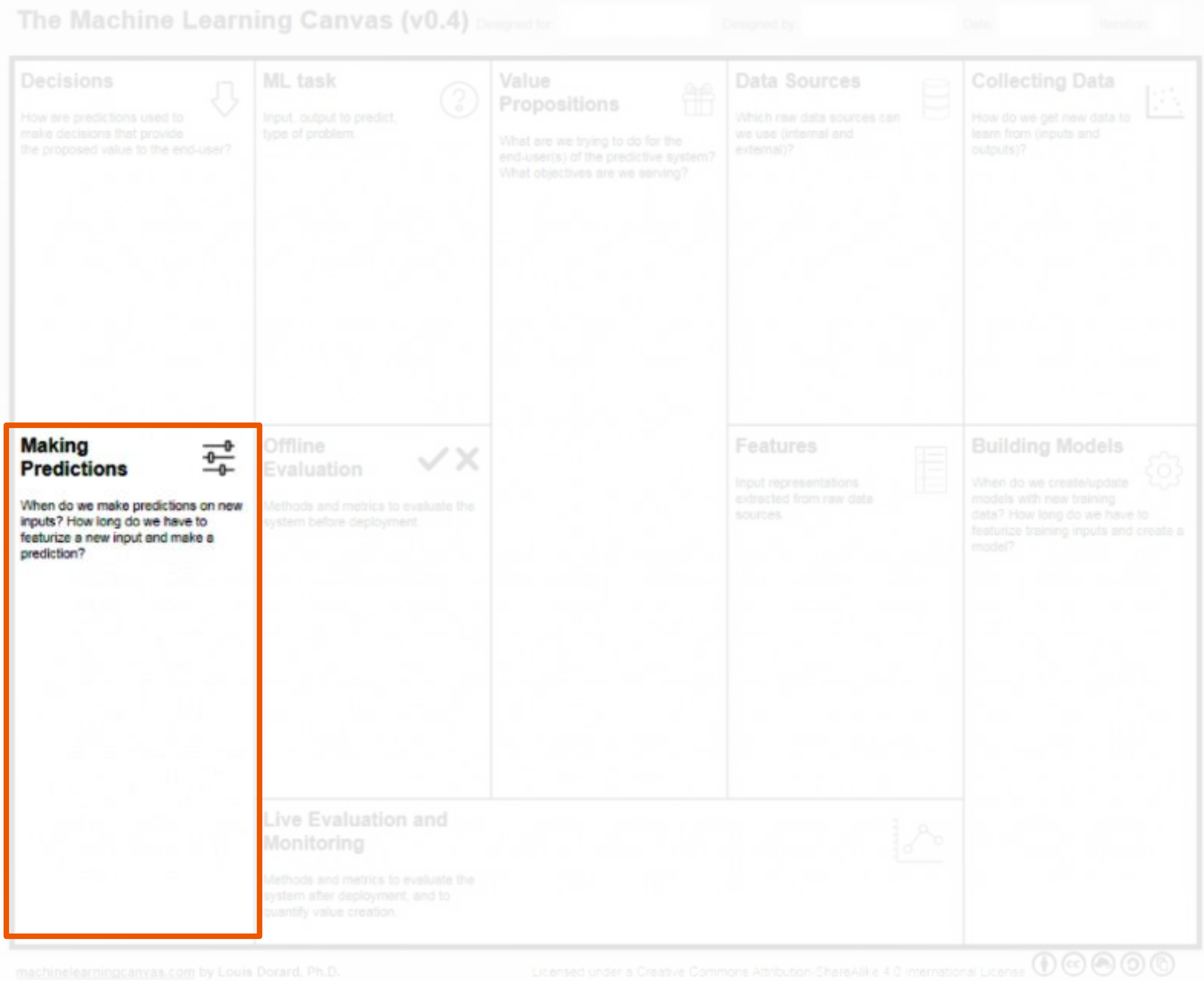
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2. Machine Learning Canvas - Making Predictions

Technical constraints on predictions made to support decisions : volume, frequency, time, etc.

Different aspects to think about:

- Frequency and volume constraints - How many predictions based on the decisions?
- Time constraints
- Monitoring in production

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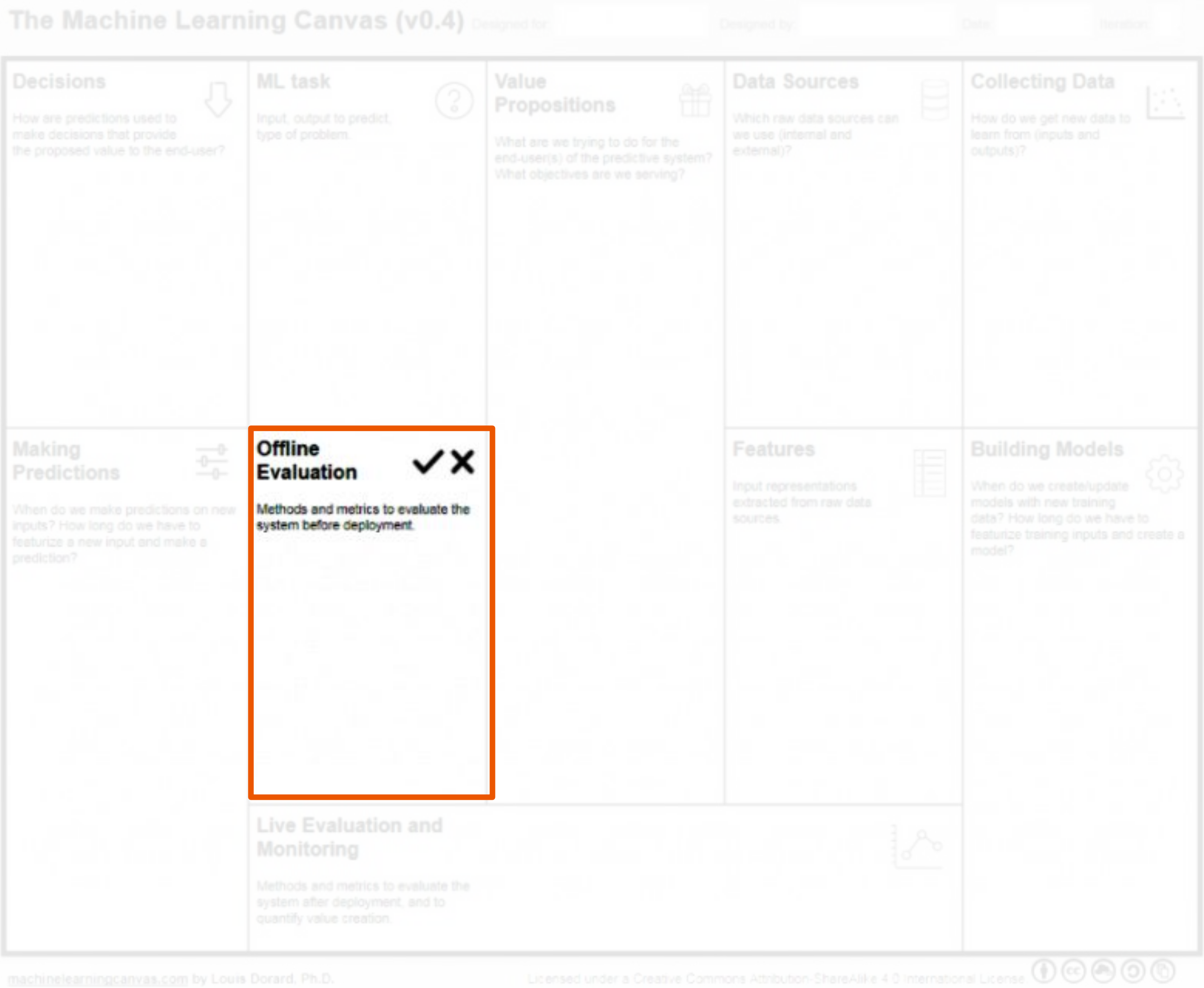
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2. Machine Learning Canvas - Offline Evaluation

Methods and metrics to evaluate the system before deployment

- How are you going to test your model?
- Datasets to evaluate performance
  - 80% Training
  - 10% Validation
  - 10% Testing
- What metrics do you use to evaluate the performance?

CAMBRIDGE SPARK

Confusion Matrix

		Prediction	
		Positive	**Negative**
Reference	**Positive**	True Positive	False Negative
	Negative	False Positive	True Negative

CAMBRIDGE SPARK

Confusion Matrix

CAMBRIDGE SPARK

Confusion Matrix

Prediction

Reference		Positive	Negative
	Positive	TP = 6	FN = 2
	Negative	FP = 3	TN = 5

CAMBRIDGE SPARK

Confusion Matrix

- Accuracy = 78,5%
- Recall (Quantity) = 75%
- Precision (Quality) = 66%
- F1 Score = 70%

Prediction

Reference		Positive	Negative
	Positive	TP = 6	FN = 2
	Negative	FP = 3	TN = 5

CAMBRIDGE SPARK

Confusion Matrix

- Accuracy = (TP+TN)/(TP+TN+FP+FN)
- Recall (Quantity) = TP / (TP+FN)
- Precision (Quality) = TP/ (TP+FP)
- F1 Score - 2x (Precision * Recall/Precision + Recall)

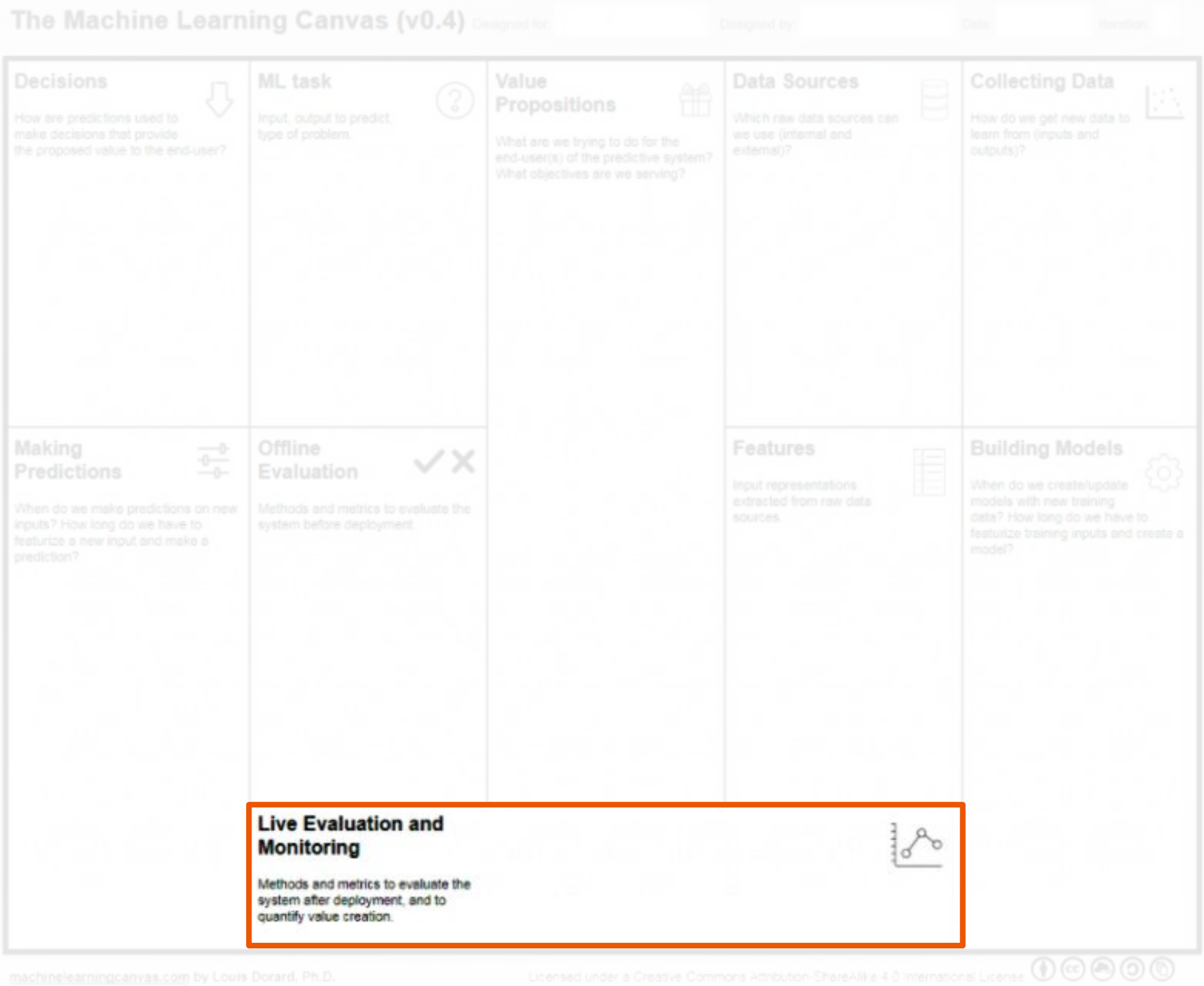
Prediction

		Positive	**Negative**
Reference	**Positive**	True Positive	False Negative
	Negative	False Positive	True Negative

What model to chose?

	Precision	Recall	F1 Score
Model 1	80%	90%	86%
Model 2	75%	82%	77%
Model 3	89%	70%	78%

CAMBRIDGE SPARK


The Machine Learning Canvas (v0.4)
Decisions
How are predictions used to make decisions that provide the proposed value to the end-user?
ML task
Input, output to predict, type of problem.
Value Propositions
What are we trying to do for the end-user(s) of the predictive system? What objectives are we serving?
Data Sources
Which raw data sources can we use (internal and external)?
Collecting Data
How do we get new data to learn from (inputs and outputs)?
Making Predictions
When do we make predictions on new inputs? How long do we have to featurize a new input and make a prediction?
Offline Evaluation
Methods and metrics to evaluate the system before deployment.
Features
Input representations extracted from raw data sources.
Building Models
When do we create/update models with new training data? How long do we have to featurize training inputs and create a model?
Live Evaluation and Monitoring
Methods and metrics to evaluate the system after deployment, and to quantify value creation.
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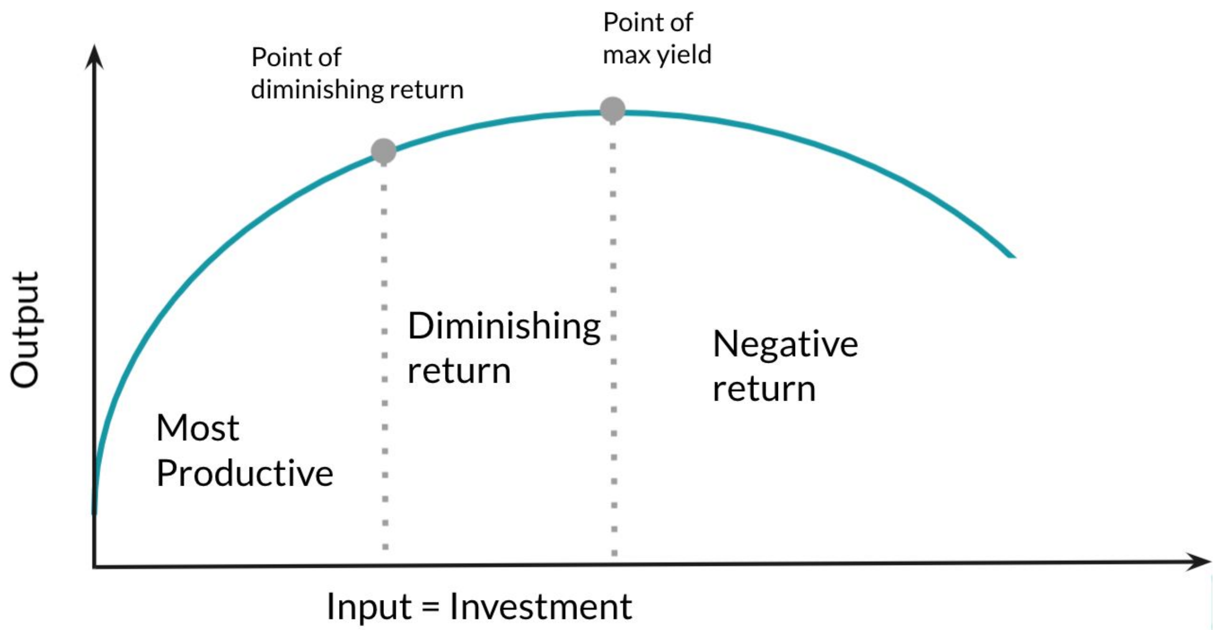
2. Machine Learning Canvas - Live Evaluation and Monitoring

Methods and metrics to evaluate the system after deployment

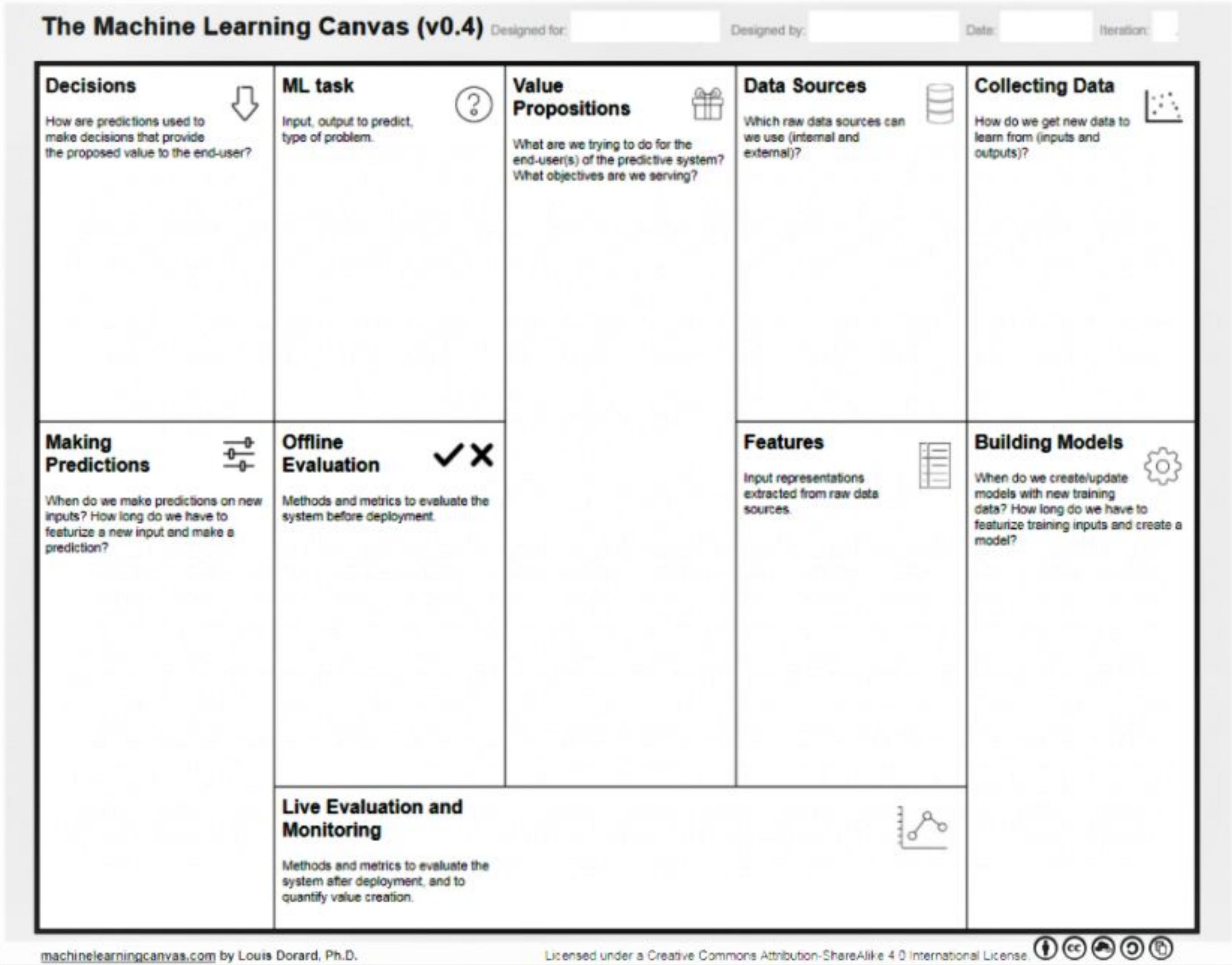
- How do you evaluate the performance and value creation of your model

CAMBRIDGE SPARK

Investments in AI Model



CAMBRIDGE SPARK



The Machine Learning Canvas (v0.4)

Designed for: Designed by: Date: Iteration:

Decisions
How are predictions used to make decisions that provide the proposed value to the end-user?

ML task
Input, output to predict, type of problem.

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The Machine Learning Canvas (v0.4)

Designed for: Designed by: Date: Iteration:

Decisions

How are predictions used to make decisions that provide the proposed value to the end-user?

Each month we randomly filter out 50% of the clients
Sort remaining by descending and show prediction path on recommendations
Send recommendation as many as suggested by simulation

ML task

Input, output to predict, type of problem.

Predict answer "Is this client going to take our recommendation?"
- Input Customer
- Output: "Took" or "Didnt' take"
- Binary classification

Value Propositions

What are we trying to do for the end-user(s) of the predictive system? What objectives are we serving?

We want to our clients to get new opportunities automatically based on recommendations based on their profile and their portfolios and interests
Improve automatically subscription to financial services

Data Sources

Which raw data sources can we use (internal and external)?

- CRM tool
- Customer Support
- Financial Services
- Customer data

Collecting Data

How do we get new data to learn from (inputs and outputs)?

Every month, we see which of last month's customers took the recommendations by looking in the database

Making Predictions

When do we make predictions on new inputs? How long do we have to featurize a new input and make a prediction?

Every month we featurize all current customers and make predictions for them

We do this overnight along with building the model that powers these predictions and evaluating it

Offline Evaluation

Methods and metrics to evaluate the system before deployment.

Before soliciting customers
- Evaluate new model accuracy on predefined profiles
- Simulate recommandation taken in the last month (using model from customers 2 month ago)

Features

Input representations extracted from raw data sources.

- Consumer info at time (age, sex, city, job…)

Event between t-1 month and t
- Recommandations taken
- Support or financial services interactions

Building Models

When do we create/update models with new training data? How long do we have to featurize training inputs and create a model?

Every month we create a new model from the previous month data set

We do this overnight with offline evaluation and making predictions

Live Evaluation and Monitoring

Methods and metrics to evaluate the system after deployment, and to quantify value creation.

- Accuracy of last month prediction on hold out set
- Compare recommandation taken and earn revenue between last month hold out set and remaining set
- Monitor (non recommended customer/ # solicitations)