Predictive Analytics from the Shelf - Next Basket Value, Churn+Conv Probabilities, Customer Lifetime Value

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Background

- Company Webtrekk/ Mapp: Tracking Web Shopping data for e.g. Deutsche Bank, Tchibo, Esprit, etc.
- Customers are not aware of the potential of their data, at the same time huge money is spent by marketing for data scientists
- Predictions for Marketing as an off-the-shelf product of the company

Use Cases (Industry perspective)

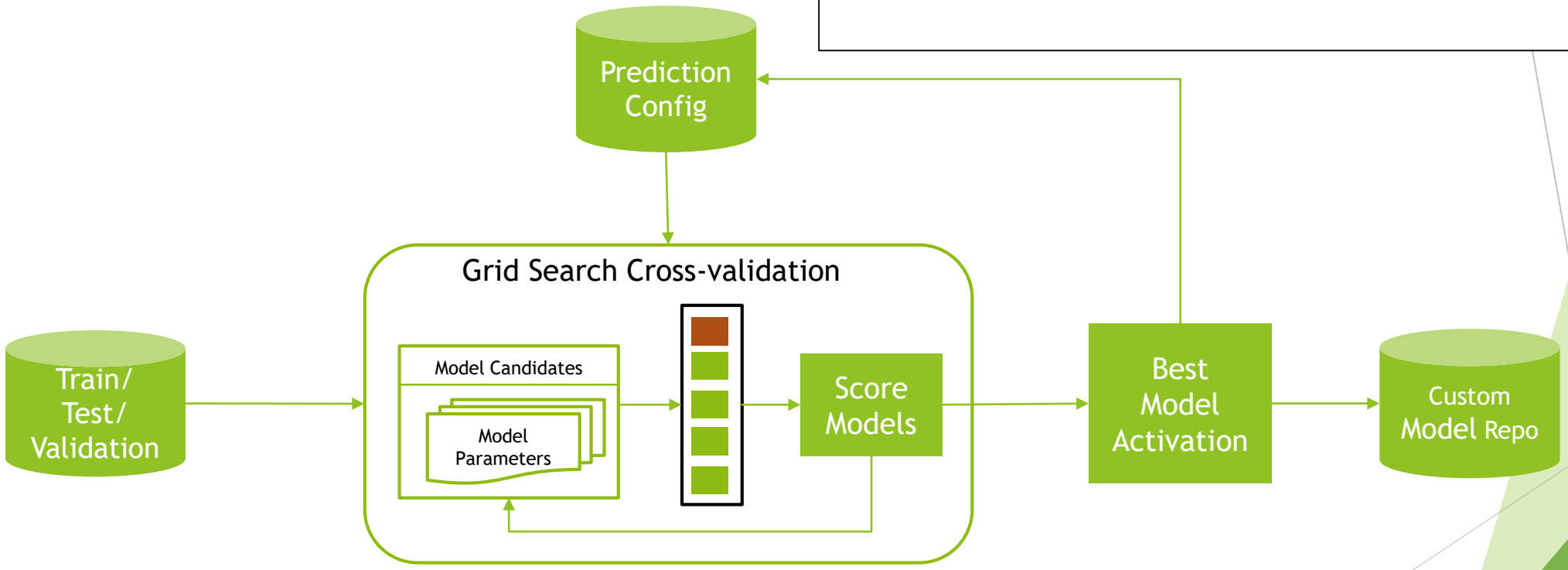
- Goal UC1: Convert high-value, low-conversion-probability users with discounts and minimal opportunity costs
- Needed UC1: Next Basket Value, Conversion Probability
- Goal UC2: Strengthen the loyalty of valuable users who are at massive risk of termination
- Needed UC2: Customer Lifetime Value, Churn Probability

Predictions: PCLV, NOV, Churn, Conv

- **Churn Probability:** The likelihood of a visitor not returning.
- **Conversion Probability:** The likelihood of a visitor to place an order within a certain time limit.
- **Next Order Value (NOV):** The expected value of the next order, which – together with the conversion probability – is a perfect proxy for the expected order value in the near future.
- **Potential Customer Lifetime Value (PCLV):** The potential customer lifetime value is defined here as the expected order value in the next year, under the condition that the customer does not churn.

Off-the-Shelf Rollout

REST Interface: The relevant Python libraries (scikit-learn, pandas, etc.) have been encapsulated to allow for algorithm choice, meta-learning, automated feature selection, and Import/ Export functionalities.



Churn Probability

The **churn probability** represents the visitor's likelihood of not returning.

- **Features:** previous visits, orders, order value, orders-per-visit, value-per-order, etc.
- **Learning:** Calibrated for a sample of all visitors based on their churn behavior in the past, using **logistic regression** by default*)
- **Quality Measurement:** e.g. MCC (Matthews Correlation Coefficient)

Conversion Probability

The **conversion probability** represents the visitor's likelihood of conversion.

- **Features:** previous visits, orders, order value, orders-per-visit, value-per-order, etc.
- **Learning:** Calibrated for a sample of all visitors based on their conversion behavior in the past, using **logistic regression** by default*)
- **Quality Measurement:** e.g. MCC (Matthews Correlation Coefficient

Next Order/ Basket Value (NOV/ NBV)

The **next order value** represents the visitor's expected next order value.

- **Features:** previous visits, orders, order value, orders-per-visit, value-per-order, etc.
- **Learning:** Calibrated for a sample of buyers based on their next order values in the past, using a weighted RFM model **with linear regression** (and sanity checks) by default*)
- **Quality Measurement:** R^2 (Coefficient of Determination) + MSE

Customer Lifetime Value

The **customer lifetime value** gives an estimate of the **expected conversion value of a buyer** in the coming year.

- **Features:** previous visits, orders, order value, orders-per-visit, value-per-order, etc.
- **Learning:** Calibrated for a sample of returning (non-churned) buyers based on their next month conversion values in the past, using **linear regression** (and sanity checks) by default*)
- **Quality Measurement:** R^2 (Coefficient of Determination) + MSE

Use Cases re-visited – can we design a solution? If not, why not?

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Deep Learning vs. Regression

- Deep Learning can learn generalized models ...
- but it requires much data for doing so
- If the data is less, the feature space must be reduced ...
- so deep learning has less or no advantage over regression
- Therefore and because deep learning provides less explanation
- ... simple algorithms which also require less energy are usually better ...
- but here is an investigation on deep learning nonetheless:

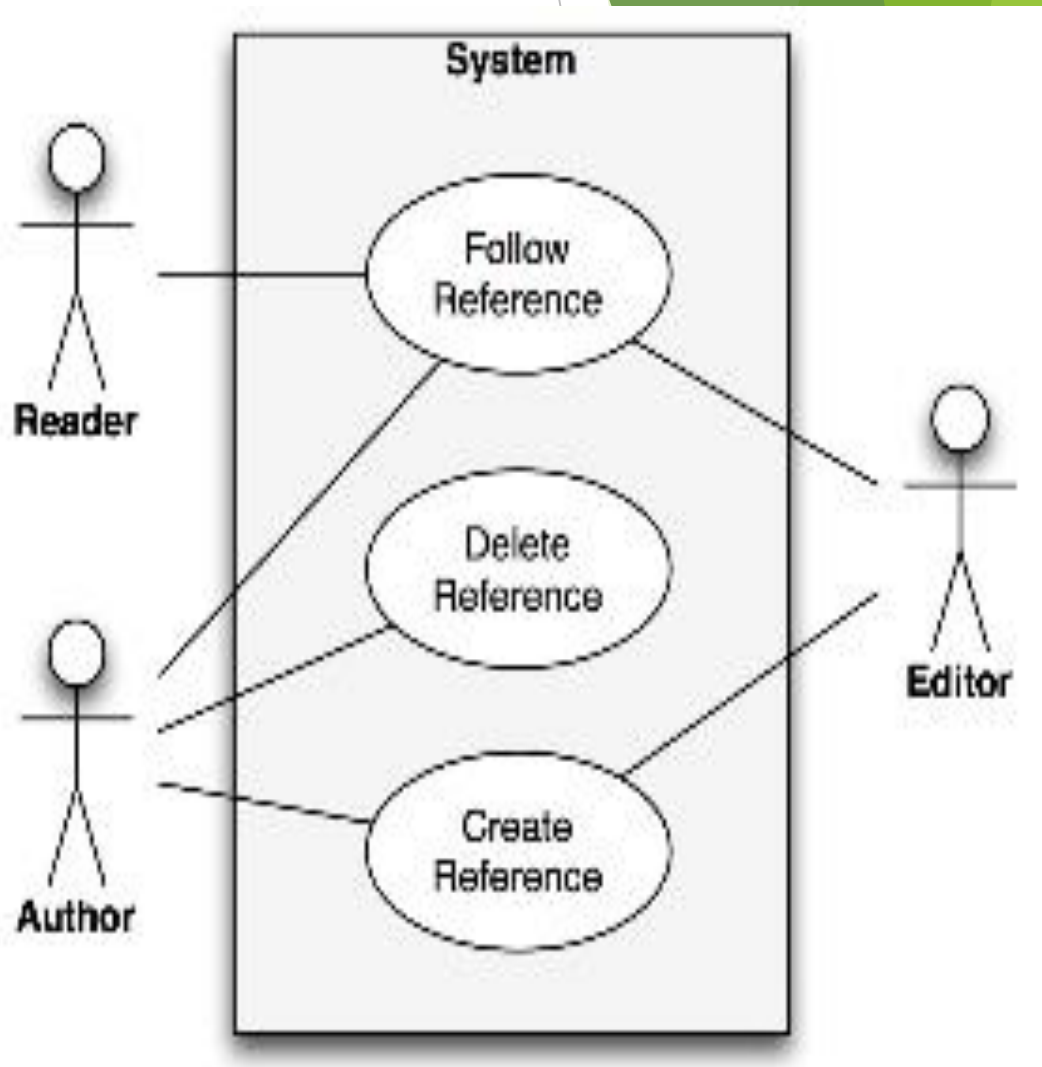
Dennis Koehn, Stefan Lessmann, Markus Schaal:
Predicting online shopping behaviour from clickstream data using deep learning. Expert Syst. Appl. 150: 113342 (2020)

Follow-Up: The perfect information marketplace (with marketing)

- In the past, marketing was also the main way to learn about products and services. In the digital age, the information about offers should be fully transparent, so that needs can be fulfilled perfectly.
- Even so, marketing may have important roles, which ones? Can we design such a market place?
- Instructions:
  - Identify User Groups, e.g. Consumers, Providers, Marketeers
  - Describe a Use Case informally
  - In Groups: Detail each use case, example on following slide

Use Case Modeling by Example

- Description: The understanding/ comprehension of paper-based documents is often aided by the inclusion of margin notes and by highlighting important sections using fluorescent marker pens. Since many people are now reading texts in electronic form, a program which can provide such aids to understanding would be a useful tool.
- Use Cases: Margin Notes (skipped), Highlighting (skipped), References (create, delete, follow)
- Use Case „Create Reference“ on next slide …



Use Case Example „Create Reference“

Name: Create Reference
Participating Actors: Author, Editor
Entry Condition: Text is opened and Editor has navigated to the source area of the planned reference.
Exit Condition: Reference is placed and can be followed.
Event Flow:

1. Editor marks text fragment (Use case: Mark Text) as source for the reference.
2. Editor selects function "Create Reference".
3. Editor navigates to destination of reference (Use case: Navigate).
4. Editor marks text fragment (Use case: Mark Text) as destination of reference.
5. Editor completes the creation of the reference and adds an explanatory text.
6. System shows the reference.