

Assignment 1:

Deep Learning Applications in Management Analytics

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1 Customer Lifetime Value - Traditional Machine Learning Approach

In business analytics, understanding and maximizing Customer Lifetime Value (CLTV) is pivotal. CLTV measures the total revenue a business can expect from a single customer account throughout the business relationship. The longer a customer's journey in a company, the greater their lifetime value becomes. Thus, accurately predicting CLV is essential for businesses to allocate marketing budgets efficiently, tailor customer relationship management strategies, and ultimately increase the return on marketing spends.

1.1 Overview of the Business Problem and Its Importance

Customer Lifetime Value indicates a customer's propensity to return, as well as their loyalty to the brand. A business with a high average CLTV is indicative of good product market fit and is a metric that can be monitored and optimized over time. Increasing recurring revenue is a target specifically for ecommerce and subscription-based businesses as it can bring in healthy cashflow, enabling investment into more long-term customer acquisition and large-scale audience targeting with marketing. In general, companies strive for a ratio of CLTV to CAC (Customer Acquisition Cost) of around 3:1, that is acquired customers should spend at least 3 times their acquisition cost. The primary challenge of predicting CLTV lies in its temporal nature - it's influenced by various factors including customer behaviors, purchase patterns, and engagement levels which can change over time. Traditional formulaic approaches to calculating CLTV, such as historical averages or heuristic models, often fail to capture these nuances, leading to suboptimal business decisions. In response, machine learning (ML) techniques have emerged as the best strategies to predict CLTV with a higher precision by leveraging large datasets and uncovering complex patterns in customer data.

1.2 Chosen Technique: Ensemble Learning Methods

In predicting Customer Lifetime Value (CLTV), ensemble models stand out for their ability to integrate predictions from multiple machine learning models, leading to improved accuracy and robustness compared to single-model approaches. The complex nature of CLTV, involving numerous variables and patterns within customer data, makes ensemble methods particularly suited for this task. The following are some of the ensemble models that work best for CLTV prediction and the reasons for their effectiveness:

1. Random Forest: By aggregating decisions from multiple decision trees, it reduces the risk of overfitting while capturing complex, non-linear relationships within customer behaviors.

2. Gradient Boosting Machines (GBM): GBM focuses on correcting the errors of previous models in the sequence, leading to a strong predictive performance where the intricacies of customer behavior are crucial. Often in CLTV prediction, a small segment of customers contributes to a large portion of the value. GBM can handle this imbalance effectively.

3. XGBoost: XGBoost is known for its efficiency and scalability, making it suitable for large datasets often involved in CLTV prediction. Comes with built-in cross-validation at each iteration, making the model tuning more efficient and effective.

4. LightGBM: Optimized for speed and memory usage, LightGBM can handle larger datasets without compromising on model performance, important for businesses with extensive customer data.

5. CatBoost : Excellently processes categorical variables directly, which are often significant in

predicting CLTV, like customer region, product categories, etc. It provides a balance between accuracy and overfitting, crucial for developing a reliable CLTV prediction model that generalizes well to unseen data. So we choose this technique among the ensemble models to build the CLTV prediction model.

1.3 Rationale Behind Selecting CatBoost

CatBoost is chosen for CLTV prediction for several reasons:

- **Learning on Categorical Data:** CatBoost handles categorical variables which are often a significant part of CLTV prediction datasets, and improving prediction accuracy without the need for extensive preprocessing.
- **Reduced Overfitting:** CatBoost includes mechanisms to combat overfitting, ensuring that the model remains generalizable and accurate on unseen data.
- **Speed:** CatBoost is designed for speed, allowing for faster model training and prediction, which is essential when dealing with large datasets common in CLTV prediction tasks.
- **Resource Utilization:** It is optimized for efficient use of computational resources, making it suitable for scenarios where hardware capabilities are a consideration.
- **Interpretability Through Feature Importance:** CatBoost provides insights into feature importance, revealing how different customer attributes influence the CLTV prediction. This information is crucial for formulating targeted business strategies.

1.4 Comparison with Alternative Ensemble Models

When evaluating CatBoost for Customer Lifetime Value (CLTV) prediction, it's beneficial to compare its performance and characteristics not only against deep learning and linear regression but also other prominent ensemble models.

Random Forest: Similar to CatBoost, Random Forest excels in handling various data types and offers significant interpretability through feature importance scores. It's robust to overfitting due to the ensemble nature of decision trees. However, unlike CatBoost, Random Forest requires manual encoding of categorical variables, which can be time taking and may lead to loss of information. It might also not be as efficient as CatBoost in terms of computation and handling large-scale data.

Gradient Boosting Machines (GBM) and XGBoost: Both are powerful ensemble techniques that sequentially correct errors from previous models, offering high accuracy in predictions. XGBoost, in particular, is known for its speed and efficiency. However, these models require extensive hyperparameter tuning to achieve optimal performance and can be prone to overfitting if not properly regularized. They also do not natively handle categorical variables as efficiently as CatBoost. CatBoost offers a balance between speed and accuracy while providing native support for categorical variables, reducing the preprocessing workload and potentially improving model performance.

LightGBM: It is designed for speed and efficiency, capable of handling large datasets with ease. It's similar to CatBoost in its approach to categorical variables, though it may work slightly differently under the hood. LightGBM can be more sensitive to overfitting compared to CatBoost, especially with smaller datasets. Its handling of categorical variables, while efficient, might not always match CatBoost's performance in specific scenarios. CatBoost balances efficiency with robustness against overfitting, making it a solid choice for both large and small datasets. It also ensures high accuracy levels, particularly with datasets featuring complex categorical relationships.

1.5 Comparison with Deep Learning Approaches:

Deep learning models can capture complex, nonlinear relationships in high-dimensional data. They are ideal for large datasets with intricate patterns. The "black box" nature makes interpretation challenging, limiting actionable business insights. CatBoost is optimized for performance, requiring significantly less computational power compared to deep learning models. This makes it a cost-effective solution for businesses without access to high-end computing resources. The efficiency of CatBoost extends to quicker model training and prediction times, enabling businesses to iterate and adapt their strategies more rapidly in response to changing market conditions or customer behaviors. CatBoost includes several mechanisms to prevent overfitting, ensuring that models generalize well to unseen data. This robustness is particularly important in CLTV prediction, where overfitting can lead to overly optimistic or skewed forecasts. In conclusion, while each model has its strengths, CatBoost's unique combination of efficiency, accuracy, and native handling of categorical variables sets it apart for CLV prediction tasks. Its balance of interpretability and predictive power makes it an excellent choice for businesses looking to leverage their customer data for strategic decision-making, providing a practical alternative to more demanding models like deep learning, and a more powerful solution compared to simpler models like linear regression.

1.6 Pros of CatBoost

- **Highly Accurate on Diverse Data:** Exceptionally performs on datasets with a mix of categorical and numerical data, directly impacting the precision of CLV predictions.
- **Interpretable Results:** Offers insights into the decision-making process, allowing businesses to understand the drivers behind CLV predictions.
- **Efficient on Large Datasets:** Capable of handling large volumes of data with a relatively low computational requirement.
- **Reduced Preprocessing Needs:** Directly processes categorical data, reducing the need for extensive data preprocessing and encoding.

1.7 Cons of CatBoost

- Requires careful tuning of parameters to achieve optimal performance, which can be time-consuming.

1.8 Impact on Business Outcomes and Performance Metrics

Implementing CatBoost for CLV prediction offers significant benefits to businesses:

Enhanced Marketing Efficiency

Identifying high-value customers allows for more focused and efficient marketing efforts, optimizing return on investment.

Improved Customer Insights

Insights from CLTV predictions aid in crafting more effective segmentation and personalization strategies, enhancing the customer experience and loyalty.

Operational Efficiency

A deeper understanding of customer value dynamics facilitates more informed decisions on resource allocation, emphasizing areas with the highest return.

Proactive Customer Management

Predicting at-risk customers enables proactive engagement strategies, bolstering retention and customer satisfaction.

1.9 Conclusion

CatBoost stands out as a powerful modelling approach for predicting Customer Lifetime Value, providing a blend of accuracy, efficiency, and interpretability. Its capabilities in handling complex, mixed-type data sets set it apart, making it an asset for businesses seeking to enhance their analytical prowess in understanding and predicting customer behavior. Leveraging CatBoost can significantly impact a company's ability to optimize marketing efforts, improve customer engagement, and drive sustained growth.

2 Deep Learning in Enhancing Brand Visibility and Engagement Through Logo Recognition

2.1 Introduction

With billions of photos shared across different social media platforms every day, the capability to analyze images for brand visibility and engagement has become a crucial aspect of marketing analytics. However, 80% of images featuring a brand's logo do not mention the brand in text, contributing to a significant gap in knowledge about how brands measure their perception. This gap emphasizes the need for technologies that can augment social listening in platforms like Instagram and TikTok, capturing the data contained in images and their descriptions to revolutionize marketing strategies and competitive analysis.

2.2 Overview of the Business Problem

Brand visibility and consumer engagement are important ROI metrics that drive marketing strategies and business growth. The vast amount of visual content shared across social media platforms offers insights into how consumers perceive and interact with brands. However, traditional text-based analytics miss out on a large portion of this data, as they cannot capture or analyze images. Deep learning, through the application of Convolutional Neural Networks (CNNs) for logo recognition, presents a solution to this challenge, enabling businesses to harness visual content for comprehensive brand analysis. CNNs are the standardly used in deep learning for recognizing images because they are particularly good at understanding complex visuals, making them perfect for spotting brand logos in the images shared online.

2.3 Rationale for using CNNs for Logo Recognition

Using CNNs for recognizing logos is supported by several key advantages:

- **Automated Feature Learning:** CNNs can automatically learn and identify features relevant to logos amidst the noise and complexity of real-world images.
- **Scalability:** With the ability to handle large datasets, CNNs are well-suited for analyzing the extensive volumes of images generated on social media platforms.
- **Accuracy:** CNNs significantly outperform traditional machine learning methods in image recognition tasks, providing more reliable insights into brand visibility and consumer engagement.

2.4 Comparison with Other Deep Learning Architectures

While there are several deep learning architectures available, there are specific reasons why CNNs are preferred over other methods for the specified task:

1. **Recurrent Neural Networks (RNNs):** RNNs excel in processing sequential data, such as text or time series, making them less suited for the spatial analysis required in image recognition. RNNs also do not naturally capture the spatial hierarchies and relationships within images, which would affect their ability to recognize logos that CNNs handle adeptly.

2. **Fully Connected Networks (FCNs):** FCNs treat input data as a flat vector, ignoring the spatial structure and relationships within images. This leads to inefficient learning and poor performance in tasks like logo detection where the arrangement of pixels and features is crucial.
3. **Autoencoders:** Designed primarily for data compression and reconstruction, learning compact representations of data. While useful for dimensionality reduction or denoising data, they are not optimized for classification or recognition tasks like logo detection.
4. **Generative Adversarial Networks (GANs):** GANs excel in generating new data samples but are less effective for classification or detection tasks. Training GANs involves balancing between two competing networks, which can be challenging and resource-intensive.

2.5 Pros of CNNs

- Ability to learn complex visual patterns autonomously.
- Scalable to extensive image datasets prevalent in social media analytics.
- Superior accuracy in identifying brand logos and analyzing image content.

2.6 Cons of CNNs

- Requires substantial computational power and large datasets for training.
- The interpretability of decisions can be complex compared to simpler models.

2.7 Impact on Business Outcomes and Performance Metrics

Implementing deep learning for logo recognition transforms brand visibility analysis and engagement strategies. It allows companies to:

- **Measure Sponsorship ROI:** By analyzing the presence and visibility of logos in event imagery, companies can accurately assess the impact of sponsorships and partnerships.
- **Understand Customer Behavior:** Logo recognition provides insights into how, when, and where products are being used, offering a direct view of consumption patterns and consumer preferences.
- **Manage Campaigns and Communities More Effectively:** Integrating image analysis with traditional metrics provides a comprehensive view of marketing campaign performance and brand presence.
- **Influencer Partnerships:** Analyzing social media posts at a large scale to check for influencers that match best with the brand, or who have used brand the most.

This model enables marketers to capture the full spectrum of brand mentions, moving beyond textual analysis to include the rich data contained in images. For example, a trend of associating a brand with certain lifestyles or activities can inform targeted marketing strategies, influencer partnerships, and product development.

2.8 Conclusion

The application of CNNs for logo recognition in brand visibility and engagement analysis represents a significant advancement in marketing analytics. By leveraging deep learning to analyze visual content, businesses can gain a holistic understanding of their brand’s presence across digital platforms. This approach not only fills the gap left by text-based analytics but also provides a more nuanced and comprehensive understanding of consumer behavior and brand interaction. As companies continue to compete for attention in an increasingly crowded digital landscape, the ability to analyze and act upon visual data will become a cornerstone of effective marketing strategies.

Arc’teryx Brand Logo Classifier using CNNs - Model Summary

Layer (type)	Output Shape	Param #
Conv2d-1	[-1, 16, 128, 128]	448
MaxPool2d-2	[-1, 16, 64, 64]	0
Conv2d-3	[-1, 32, 64, 64]	4,640
MaxPool2d-4	[-1, 32, 32, 32]	0
Conv2d-5	[-1, 64, 32, 32]	18,496
MaxPool2d-6	[-1, 64, 16, 16]	0
Linear-7	[-1, 512]	8,389,120
Dropout-8	[-1, 512]	0
Linear-9	[-1, 2]	1,026
Total params: 8,413,730		
Trainable params: 8,413,730		
Non-trainable params: 0		
Input size (MB): 0.19		
Forward/backward pass size (MB): 4.38		
Params size (MB): 32.10		
Estimated Total Size (MB): 36.67		

References

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