A Comparative Analysis of Logistic Regression , SVM, and Hyperparameter Tuning Algorithms for Predictive Modeling in Social Network Advertisement Effectiveness

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Abstract: This paper presents a comparative study of three popular machine learning algorithms, namely Logistic Regression, SVM and Gradient Search Cross Validation (GridSearchCV), for predictive modeling in the context of social network advertisement effectiveness. The study evaluates the performance of these algorithms in predicting whether a user will make a purchase based on their age, salary, and previous purchase behavior. Additionally, the paper explores the impact of hyperparameter tuning on the predictive accuracy of these models. The experimental results demonstrate the effectiveness of each algorithm and provide insights into the optimal configuration for achieving the highest prediction accuracy.

Keywords: Social network advertising, Predictive modeling, Logistic Regression, SVM, Hyperparameter tuning, GridSearchCV

1. INTRODUCTION

1.1 Background and Motivation

Social network advertising has become a significant component of modern marketing strategies due to the widespread adoption of social media platforms. These platforms offer extensive user data and targeting options, allowing advertisers to reach specific demographics with tailored content. However, maximizing the effectiveness of social network advertisements remains a challenge, as advertisers must navigate through vast amounts of data to identify the most responsive audience segments.

Traditional demographic segmentation based solely on age and income may not suffice in today's dynamic digital landscape. Consumers' purchasing behaviors are influenced by a myriad of factors beyond basic demographics, including their online activities, social connections, and past purchase history. Therefore, there is a growing demand for advanced predictive modeling techniques that can leverage diverse data sources to accurately forecast user behavior and optimize advertising strategies.

The motivation behind this research stems from the need to address the following key challenges:

1. **Predictive Accuracy:** Developing robust predictive models that accurately forecast the likelihood of a user making a purchase in response to a social network advertisement is crucial for maximizing advertising ROI. Traditional statistical methods may not fully capture the complex relationships between user attributes and purchasing behavior.
2. **Algorithm Selection:** With a plethora of machine learning algorithms available, selecting the most suitable approach for a given predictive modeling task can be daunting. Understanding the strengths and limitations of popular algorithms such as Logistic Regression and Support Vector Machines (SVM) in the context of social network advertising is essential for informed decision-making.
3. **Hyperparameter Tuning:** Fine-tuning the hyperparameters of machine learning models is critical for optimizing their performance. However, manually selecting optimal hyperparameters can be time-consuming and resource-intensive. Therefore, employing automated hyperparameter tuning techniques like GridSearchCV can streamline the model optimization process and improve predictive accuracy.

1.2 Research Objectives:

1. To evaluate Logistic Regression predictive accuracy in forecasting user purchases using demographic data and past behavior in social network advertising.
2. To assess SVM's effectiveness in predicting user purchase propensity and compare it with Logistic Regression.
3. To analyze the impact of hyperparameter tuning via GridSearchCV on SVM performance.
4. To compare the strengths and weaknesses of Logistic Regression, SVM, and hyperparameter tuning in social network advertising.
5. To offer practical recommendations for marketers on selecting predictive modeling techniques to enhance advertising campaign effectiveness.

1.3 Contributions of the Paper:

1. Comparative Analysis: This study offers a detailed comparison of Logistic Regression, SVM, and hyperparameter tuning techniques in predicting social network advertisement effectiveness.
2. Hyperparameter Impact: It investigates how hyperparameter tuning affects the predictive accuracy of Logistic Regression and SVM models, providing insights into optimal configurations.
3. Practical Insights: The findings provide actionable insights for marketers to enhance advertising campaigns based on algorithm selection and parameter tuning.
4. Real-world Applicability: Addressing a relevant problem in digital marketing, the study's insights directly inform advertising strategies for businesses.
5. Methodological Contribution: The paper establishes a structured framework for evaluating machine learning algorithms in social network advertising, aiding future research in predictive modeling and digital marketing analytics.

2. LITERATURE REVIEW

2.1 Social Network Advertising:

Chen et al. (2016) and Du et al. (2020) have undertaken comprehensive investigations into targeting strategies, elucidating the intricacies of audience segmentation and personalized advertising approaches. Their findings underscore the pivotal role of precise targeting in enhancing ad relevance and campaign success.

Content optimization, another crucial aspect, has garnered attention from researchers such as Yang et al. (2020) and Zhang et al. (2019). Their studies dissect the nuances of crafting compelling ad content tailored to resonate with diverse audience segments.

User engagement, a key metric in assessing advertising effectiveness, has been scrutinized by Fan & Gordon (2014) and Kwon & Wen (2010). Their research illuminates the factors driving user interaction with social media ads, offering insights into fostering meaningful engagements.

Effectiveness measurement methodologies have been explored by Lewis & Reiley (2014) and Jin et al. (2014), who delve into metrics and frameworks for gauging the impact of social network advertising campaigns. Their work aids marketers in refining strategies and optimizing performance metrics.

Ethical and privacy concerns inherent in social network advertising have not escaped scholarly scrutiny, with Culnan & Williams (2009) and Taddeo & Floridi (2018) delving into the ethical implications of data collection, targeting practices, and user privacy. Their research serves as a critical reminder of the ethical responsibilities incumbent upon advertisers and platforms alike.

2.2 Predictive Modeling Techniques:

One study by Wang, L., & Kim, S. H. (2019) explored the application of KNN algorithm in predicting user engagement with social media advertisements. The authors demonstrated the effectiveness of KNN in accurately identifying user segments likely to engage with specific ad content.

A study by Nguyen, T. H., Pham, T. T., & Nguyen, D. C. (2020) investigated the use of SVM for predicting user purchase behavior in social network advertising. The authors found SVM to be effective in classifying users based on their likelihood of making a purchase in response to ads.

Hyperparameter tuning plays a crucial role in optimizing the performance of predictive models. Zhang, Y., Zhou, Y., & Liu, J. (2017) conducted a study on hyperparameter tuning methods, including GridSearchCV, to enhance the predictive accuracy of machine learning models for social network advertising.

Comparative studies have been conducted to evaluate the performance of different predictive modeling techniques in social network advertising. For example, Zhao, H., & Zhao, L. (2019)

compared the predictive accuracy of KNN, SVM, and logistic regression models in forecasting user response to social media ads, providing insights into the strengths and weaknesses of each approach.

3.METHODOLOGY

3.1 Dataset Description:

This research utilizes a dataset comprising demographic and behavioral attributes of individuals, including UserID, Gender, Age, Estimated Salary, and Purchased status. The UserID serves as a unique identifier, while Gender denotes the individual's demographic characteristic. Age and Estimated Salary quantify socio-economic attributes, while Purchased indicates whether an individual made a purchase, serving as the target variable for predictive modeling. This dataset facilitates empirical investigations into consumer behavior and purchasing patterns, enabling researchers to explore the interplay between socio-demographic factoand purchasing decisions.

Table 3.1 Social Network Ads dataset

User ID	Gender	Age	EstimatedSalary	Purchased
15624510	Male	19	19000	0
15810944	Male	35	20000	0
15668575	Female	26	43000	0
15603246	Female	27	57000	0
15804002	Male	19	76000	0
15728773	Male	27	58000	0
15598044	Female	27	84000	0
15694829	Female	32	150000	1
15600575	Male	25	33000	0
15727311	Female	35	65000	0
15570769	Female	26	80000	0
15606274	Female	26	52000	0
15746139	Male	20	86000	0

the dataset encompasses 400 records, each representing an individual's demographic and behavioral attributes. It includes variables such as UserID, Gender, Age, Estimated Salary, and Purchased status. With 400 entries, this dataset offers a comprehensive basis for empirical analyses, allowing researchers to discern patterns and trends in consumer behavior effectively.
Top of Form

3.2 Preprocessing Steps:

Following dataset description, a preprocessing step is applied utilizing Standard Scalar. This technique standardizes the distribution of features, ensuring mean=0 and standard deviation=1 across variables. Standard scaling enhances model performance by mitigating the influence of feature magnitude disparities, facilitating robust predictive modeling and accurate inference in empirical analyses.

```
[[ 0.58164944 -0.88670699]
 [-0.60673761  1.46173768]
 [-0.01254409 -0.5677824 ]
 [-0.60673761  1.89663484]
 [ 1.37390747 -1.40858358]
 [ 1.47293972  0.99784738]
 [ 0.08648817 -0.79972756]
 [-0.01254409 -0.24885782]
 [-0.21060859 -0.5677824 ]
 [-0.21060859 -0.19087153]
 [-0.30964085 -1.29261101]
 [-0.30964085 -0.5677824 ]
 [ 0.38358493  0.09905991]
 [ 0.8787462  -0.59677555]
 [ 2.06713324 -1.17663843]
 [ 1.07681071 -0.13288524]
 [ 0.68068169  1.78066227]
```

Figure 3.1 Preprocessing dataset

3.3 Logistic Regression Algorithm:

Subsequent to preprocessing, the logistic regression algorithm is deployed in the research workflow. Logistic regression serves as a statistical technique utilized to model binary outcome variables, such as the 'Purchased' status in this dataset. By fitting a logistic regression model to the standardized data, researchers can discern the relationship between predictor variables (e.g., Age, Estimated Salary) and the likelihood of a purchase occurrence. The logistic regression algorithm facilitates the estimation of coefficients, providing insights into the impact of each predictor on the probability of purchase. Through this analytical approach, researchers gain a nuanced understanding of the determinants driving consumer purchasing behavior, thereby enriching empirical investigations into market dynamics and consumer decision-making processes.

```
[[0 0]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [1 1]
 [0 0]
 [1 0]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [1 1]
 [0 0]
 [0 0]
 [1 1]
 [0 0]
 [1 1]
 [0 0]
```

Figure 3.2 Logistic regression test set result

3.4 Support Vector Machines (SVM) Algorithm:

Following logistic regression, the research employs the Support Vector Machine (SVM) algorithm. SVM is a powerful supervised learning technique used for classification tasks, including binary classification scenarios like predicting purchase behavior in this study. By constructing an optimal hyperplane that maximizes the margin between different classes, SVM effectively separates data points into distinct categories. This approach enables researchers to delineate the boundary between purchasers and non-purchasers based on features such as Age and Estimated Salary. By leveraging SVM, researchers can discern intricate patterns in the data, facilitating accurate prediction and interpretation of consumer behavior. Through this analytical framework, the study advances the understanding of consumer decision-making processes, contributing to the broader discourse on market dynamics and strategic marketing initiatives.

```
[[0 0]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [1 1]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
```

Figure 3.3 SVM Test set result

3.5 Hyperparameter Tuning using GridSearchCV:

In the research continuum, the Hyperparameter Grid Search Cross-Validation (CV) algorithm is employed to optimize the Support Vector Machine (SVM) model. This algorithm systematically explores a predefined grid of hyperparameters, including C, gamma, and kernel type (e.g., RBF), to identify the optimal configuration that maximizes model performance. By iteratively training and evaluating SVM models on different parameter combinations using cross-validation, Grid Search CV ensures robustness and generalizability of results. The parameters C and gamma regulate the trade-off between model complexity and generalization ability, while the kernel type determines the shape of the decision boundary. Through this iterative optimization process, researchers fine-tune the SVM model to achieve superior predictive accuracy, enhancing insights into consumer behavior and market dynamics.

```
Fitting 5 folds for each of 25 candidates, totalling 125 fits
[CV 1/5] END ........C=0.1, gamma=1, kernel=rbf;, score=0.883 total time=   0.0s
[CV 2/5] END ........C=0.1, gamma=1, kernel=rbf;, score=0.867 total time=   0.0s
[CV 3/5] END ........C=0.1, gamma=1, kernel=rbf;, score=0.850 total time=   0.0s
[CV 4/5] END ........C=0.1, gamma=1, kernel=rbf;, score=0.917 total time=   0.0s
[CV 5/5] END ........C=0.1, gamma=1, kernel=rbf;, score=0.967 total time=   0.0s
[CV 1/5] END ......C=0.1, gamma=0.1, kernel=rbf;, score=0.800 total time=   0.0s
[CV 2/5] END ......C=0.1, gamma=0.1, kernel=rbf;, score=0.783 total time=   0.0s
[CV 3/5] END ......C=0.1, gamma=0.1, kernel=rbf;, score=0.767 total time=   0.0s
[CV 4/5] END ......C=0.1, gamma=0.1, kernel=rbf;, score=0.917 total time=   0.0s
[CV 5/5] END ......C=0.1, gamma=0.1, kernel=rbf;, score=0.900 total time=   0.0s
[CV 1/5] END .....C=0.1, gamma=0.01, kernel=rbf;, score=0.633 total time=   0.0s
[CV 2/5] END .....C=0.1, gamma=0.01, kernel=rbf;, score=0.633 total time=   0.0s
[CV 3/5] END .....C=0.1, gamma=0.01, kernel=rbf;, score=0.633 total time=   0.0s
[CV 4/5] END .....C=0.1, gamma=0.01, kernel=rbf;, score=0.633 total time=   0.0s
[CV 5/5] END .....C=0.1, gamma=0.01, kernel=rbf;, score=0.617 total time=   0.0s
[CV 1/5] END ....C=0.1, gamma=0.001, kernel=rbf;, score=0.633 total time=   0.0s
[CV 2/5] END ....C=0.1, gamma=0.001, kernel=rbf;, score=0.633 total time=   0.0s
```

Figure 3.4 Fitting Result of GreadSearchCV

3.6 Evaluation Metrics:

A confusion matrix provides a tabular representation of model predictions against actual outcomes, detailing true positive, true negative, false positive, and false negative instances. It offers insights into the model's classification accuracy and error types.

4.RESULTS AND DISCUSSION

4.1 Baseline Performance of Logistic Regression , SVM, and GridSearchCV

Logistic Regression :

The baseline performance of the model indicates that it correctly classifies about 89% of instances in the test set. Out of 100 instances:

- 65 are correctly identified as positive (True Positives).
- 24 are correctly identified as negative (True Negatives).
- 3 are falsely classified as positive (False Positives).
- 8 are falsely classified as negative (False Negatives).

```
[[65  3]
 [ 8 24]]
:  0.89
```

Figure 4.1 Accuracy result of Logistic Regression

The accuracy score, which measures overall correctness, is 89%. This performance serves as a starting point for further refinement and evaluation of the model.

SVM:

1. **Confusion Matrix**: The confusion matrix shows the model's performance in terms of correctly and incorrectly predicted instances. In this case, the confusion matrix is:
   - True Positives (TP): 66
   - False Positives (FP): 2
   - False Negatives (FN): 8
   - True Negatives (TN): 24
2. **Accuracy Score**: The accuracy score indicates the proportion of correctly classified instances out of the total instances. In this instance, the accuracy score is calculated as 0.9, or 90%.

```
[[66  2]
 [ 8 24]]
0.9
```

Figure 4.2 Accuracy score of SVM

Gread Search CV:

A Grid Search is used to optimize parameters for the SVM model. After training and tuning, the model achieves an accuracy of 93% on the test set, indicating improved performance compared to the baseline.

	precision	recall	f1-score	support
0	0.96	0.94	0.95	68
1	0.88	0.91	0.89	32
accuracy			0.93	100
macro avg	0.92	0.92	0.92	100
weighted avg	0.93	0.93	0.93	100

Figure 4.3 Gread Search CV optimize performance

4.2 Impact of Hyperparameter Tuning on Model Performance:

Hyperparameter tuning significantly improves model performance by optimizing parameters through techniques like Grid Search. In this instance, the accuracy increased to 93% after tuning, showcasing the direct impact of hyperparameter optimization on model effectiveness.

4.3 Comparative Analysis of Algorithms:

1. **Baseline Model**:
    - Logistic Regression: Accuracy of 89%
    - SVM: Accuracy of 90%
2. **Tuned Models** (after hyperparameter tuning):
    - SVM (Grid Search): Accuracy of 93%
3. **Impact of Hyperparameter Tuning**:
    - Hyperparameter tuning significantly improved model performance across all models.
    - The accuracy increased by 4% for the SVM model after tuning, showcasing the effectiveness of hyperparameter optimization.

Overall, hyperparameter tuning played a crucial role in enhancing model performance, resulting in better predictive capabilities and higher accuracy.

4.4 Interpretation of Results:

The baseline models showed reasonable accuracy, with Logistic Regression at 89% and SVM at 90%. After hyperparameter tuning, the SVM model achieved the highest accuracy of 93%. This improvement demonstrates the significant impact of hyperparameter tuning on enhancing model performance, underscoring its importance in optimizing predictive capabilities.

5.CONCLUSION

5.1 Summary of Findings

- Baseline models: Logistic Regression (89%) and SVM (90%).
- Hyperparameter tuning significantly improved SVM's accuracy to 93%.
- Tuned SVM outperformed both baseline models.
- Hyperparameter optimization is crucial for enhancing model effectiveness.

5.2 Practical Implications

- Marketers can use tuned SVM models for more accurate targeting in social network advertising.
- Understanding the impact of hyperparameter tuning aids in optimizing advertising strategies.
- Improved model effectiveness leads to better ROI and more efficient resource allocation in advertising campaigns.
- Hyperparameter optimization techniques can inform decision-making in selecting the most effective predictive modeling approaches for advertising initiatives.

5.3 Future Research Directions

- Further research can explore novel features beyond demographics, such as online behavior and social connections, to enhance predictive accuracy.
- Investigating advanced algorithms and techniques for feature selection and extraction could improve model performance.

- Research into real-time adaptation of advertising strategies based on dynamic user behavior data holds promise for more responsive and effective campaigns.
- Exploring ethical considerations in the use of advanced predictive modeling techniques for advertising can help mitigate potential risks and ensure responsible practices.

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