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# Enterprise Sales Compensation Optimization: A Machine Learning Framework for Accurate Payout Forecasting

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## Abstract

This research develops and evaluates machine learning models for predicting sales compensation payouts based on key performance metrics. Using a comprehensive dataset of sales performance indicators, three regression algorithms were systematically compared to identify the optimal predictive model for compensation administration systems. Research Significance: Sales compensation prediction is critical for organizational budgeting, performance management, and ensuring fair compensation structures. Traditional manual calculation methods are prone to errors and inefficiencies, making automated predictive models essential for modern sales operations. This study addresses the need for accurate, data-driven compensation forecasting systems that can enhance transparency and reliability in sales management processes. Methodology: Algorithm Analysis Three machine learning algorithms were implemented and evaluated: Random Forest Regressor (RFR), AdaBoost Regressor (ABR), and Gradient Boosting Regressor (GBR). Models were trained on historical sales data and validated using standard train-test split methodology. Performance was assessed using multiple regression metrics including $R^2$, RMSE, MAE, and additional error measures to ensure comprehensive evaluation. Input Parameters: Sales Volume, Number of Deals, Average Deal Size. Output Parameter: Compensation Payout Results: Gradient Boosting Regressor demonstrated superior performance with perfect training accuracy and excellent generalization capability. The analysis revealed strong correlation between sales volume and compensation, validating performance-based incentive structures. All models showed acceptable predictive accuracy, with GBR providing the most reliable compensation forecasting.

**Keywords**: Sales compensation prediction, machine learning, gradient boosting, performance metrics, regression analysis, compensation modeling, sales analytics, predictive modeling.

## Introduction

This case study mainly examined the financial and socio-technical challenges that decision-makers face when migrating IT systems to the cloud. The infrastructure-as-a-service (IaaS) layer of the cloud is considered the most accessible for enterprises because it allows them to move their systems to the cloud with minimal or no changes to their existing applications. Companies are gravitating toward cloud-based services because providers advertise them as offering financial and technological advantages over in-house data centers. Furthermore, there is limited published research on the impact of cloud computing from a company or organizational standpoint. From an organizational perspective, the Cloud Security Alliance's extensive reports highlight that security, legal, and privacy concerns pose significant risks. The technical manager and support engineer roles within the company realized a net negative benefit. Companies can also adopt the stakeholder impact analysis methodology internally to develop a personalized understanding of their specific environment. [1] Despite strong interest, moving enterprise applications to the cloud remains a considerable challenge. Hybrid architectures provide organizations with the flexibility to make informed decisions and help strike the optimal balance between privacy, performance, and cost-effectiveness. External users can be served via cloud-based servers, while internal users can be supported through on-premise infrastructure. The difficulty arises because enterprise applications are composed of numerous interconnected components, as demonstrated by an analysis of systems used in global Fortune 100 companies. Access to servers hosting enterprise applications is typically tightly controlled, with security and access policies often embedded in low-level device configurations. Companies run a variety of applications to manage their daily operations – for example, payroll, travel, and expense reimbursement systems. [2] The classification and subsequent analysis provide insights into how innovation orientations relate to an organization's culture. A significant number of seafood retail businesses are run by individuals with a dominant English language and non-English speaking backgrounds. To examine the innovation orientation of small and medium-sized enterprises in a sector that is relatively less driven by technological progress.

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They are more affordable to adopt, can be implemented more quickly than radical innovations, and may contribute to the development of more competitive and profitable small and medium-sized enterprises. Over time, companies have invested in various infrastructure services, typically providing enterprise-wide communication and standardized support functions. Data and enterprise systems are supported by a layer of infrastructure services designed to maintain security, reliability, performance, and accessibility within the enterprise. Collectively, core databases, enterprise applications, middleware, and infrastructure services make up the corporate IT infrastructure. [3,4] Request arrivals show time-of-day fluctuations typical of many enterprise workloads, with the volume varying significantly over short time intervals. In contrast,

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LLC issues must be resolved promptly due to the rapidly changing nature of organizational workloads. We calculated the power consumption in watts by multiplying the measured current with the rated wall supply voltage. [5] In an evolving environment, the salesperson's role will expand beyond that of a general manager, to include coordinating internal and external resources to meet customer needs and expectations. Although sales automation has become increasingly integral to companies' sales strategies, it has often been overlooked by sales researchers. A shift is occurring with the decline of traditional product-based sales forces and the rise of sales automation, customer-centric sales models, and global account management.

The rise in national accounts was driven by the expansion of purchasing institutions. The implications of these changes for both practical applications and academic research are also explored. [6] Since the macro-level contribution of small firms is often represented by sales revenue, sales growth was used as a measure. Improvement in sales performance can serve as a strong indicator of a business's ability to adapt and respond to market conditions. One-way ANOVA tests were conducted to compare sales growth performance among businesses with different managerial leadership styles in the years prior to and following implementation. The achievement-oriented style that exemplifies this approach, while being the least adopted management style, has been linked to higher sales growth." Furthermore, incorporating additional performance metrics such as profitability and efficiency ratios can provide a more complete view of business performance.[7] I would like to express my sincere gratitude to the Assistant Manager of the Sales Team and the Key Account Manager for warmly welcoming me as part of their team and providing me with all the support I needed. While working with the sales team, I regularly conducted sales visits to government agencies, individual clients, and public and private organizations. I conducted sales visits to follow up with existing clients, and prepared proposal letters for prospective clients. I was also fortunate to contribute to several improvements in the sales process and team operations. The sales leader is a very supportive and encouraging person, and his insightful suggestions and ideas were truly useful to me. [8] For companies competing in increasingly competitive job markets, creating and delivering comprehensive compensation packages has become a key strategic differentiator. A top priority in this environment is implementing integrated compensation systems, as the complexity and speed of today's corporate environment cannot be managed using spreadsheets, outdated tools, or multiple disconnected platforms.

There are many valid reasons to upgrade payroll management, and those using advanced payroll systems often experience clear benefits, such as improved financial oversight. Compensation modules stand out for providing organizations with the control and flexibility they need, and supporting both traditional and highly tailored compensation approaches. An effective rewards program significantly increases employee engagement and retention. Employees who are paid fairly, recognized for their contributions, and supported in both their personal well-being and career goals are more likely to be committed, productive, and loyal. [9] We begin by outlining the historical background of organizational structures, followed by examining their key features to understand their business value. For most companies using computers, a fully integrated information system across the enterprise remained an unattainable goal. Due to various historical, technological, and economic factors, software packages have traditionally been more easily adopted by smaller organizations than by larger ones. At the societal level, the rise of enterprise systems represents a comprehensive transformation of enterprise IT infrastructure. [10] Enterprise software sales cycles typically last more than a year, allowing sales reps significant influence over the specific quarter in which a deal is finalized. After acquiring enterprise software licenses, customers typically invest over a period of a year or more in customizing the software and integrating it with their existing IT systems. Like other large-scale purchasing organizations, enterprise software sales negotiations often focus more on discount percentages from list price than on the actual amount paid.

This data includes all software products offered by a vendor with highly complex product lines, similar to the products of most major enterprise software providers. This may occur because nearly all enterprise software vendors use time-based, non-linear compensation structures, and corporate customers are accustomed to negotiating within these terms. [11] The importance of incorporating key features of real-world compensation structures when assessing and improving sales force performance highlights the need for further empirical research. It is essential to accurately consider these dynamics in order to effectively assess and improve the sales force structure.

This paper has two primary objectives. First, it introduces a framework for assessing the dynamic impact of compensation agreements on sales agent performance. Building on the insights of Copeland and Monnet (2009), we illustrate how temporal linkages can be used to infer effort from sales data in the context of sales-force compensation. Personal selling, conducted by sales force agents, introduces a number of factors that require a unique model, analytical approach, and empirical strategy compared to the context presented by Copeland and Monnet. [12] A salesperson's interactions with her peers are greatly influenced by the company's organizational boundaries and compensation structure. For example, commission-based pay encourages her to compete with peers who represent other brands. Our findings show that following a pay change, the direction of peer effects for each brand changes in a manner consistent with our main results, and that employee turnover does not show an unusual increase in the following months. Our analysis shows that both the direction and strength of peer influence are closely tied to the type of compensation system. In IC counters, peer effects among salespeople are negative, indicating competitive behavior within the same counter. [13] This includes policies such as stock ownership and new director incentives. We begin by comparing each company's compensation policy on a yearly basis to observe internal trends over time. Stock-based rewards are typically the primary form of director compensation. Developing logistics centers and workforce development, top-level compensation, and training initiatives. Talent should be categorized into tears and management pay should be allocated appropriately. [14] It is widely recognized that strong incentives can lead to unintended consequences, as employees may engage in unexpected behaviors to increase their earnings. A notable example is the manipulation of nonlinear, time-based compensation structures, in which employees are encouraged to change work hours to take advantage of irregularities in the pay schedule. The impact of employee tenure on the probability that salespeople will manipulate the compensation system, and variations in the level of customer involvement in such manipulation. [15].

## Materials and Method

Sales Volume: Sales volume is one of the most critical performance indicators for any business, representing the total revenue generated from product or service sales over a given period. It serves as a direct measure of market demand, business health, and the effectiveness of sales and marketing strategies. Tracking sales volume enables organizations to identify trends, seasonality, and customer preferences. A consistent increase in sales volume often reflects successful promotional campaigns, a well-performing sales team, or expanding market share. Conversely, declining sales volume can be a signal of changing customer behavior, increased competition, or ineffective sales strategies. Sales volume also plays a crucial role in financial forecasting, budgeting, and strategic planning.

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**Number of Deals**: The number of deals refers to the total count of successfully closed transactions within a particular time frame. This metric provides insight into the level of activity and efficiency within the sales team. A high number of deals typically indicates effective lead generation and sales process execution. However, it is important to analyze this number in context. For example, a high deal count with low overall revenue may suggest that the deals are small or low-value. Evaluating the number of deals alongside other metrics helps assess team productivity, pipeline conversion rates, and customer acquisition efforts. Additionally, it can highlight the performance of individual sales representatives and assist in setting realistic sales targets.

Average Deal Size: Average deal size is calculated by dividing total sales revenue by the number of deals closed. This metric is essential for understanding the typical value of a customer transaction and for determining the focus of sales efforts—whether on volume-driven strategies or high-value engagements. A growing average deal size can indicate successful upselling and cross-selling strategies or a shift toward premium offerings. It can also suggest that sales teams are effectively identifying and targeting more lucrative customer segments. Monitoring average deal size helps organizations adjust pricing models, evaluate the effectiveness of sales campaigns, and allocate resources to maximize return on investment.

**Compensation Payout**: Compensation payout refers to the total financial rewards given to the sales team, usually based on performance outcomes such as revenue generated, number of deals closed, or other key performance indicators (KPIs). A well-structured compensation plan is vital for motivating and retaining top talent within the sales team. It should align individual goals with company objectives to encourage behaviors that drive business growth. Compensation can include base salary, commission, bonuses, and non-monetary incentives. Monitoring payout trends also allows businesses to ensure that incentive plans are financially sustainable and delivering the desired outcomes. When aligned correctly, compensation serves as a powerful tool to increase productivity, foster healthy competition, and enhance team morale.

## Machine Learning Algorithms

**Random Forest Regression**: Random Forest Regression is an ensemble learning technique that builds multiple decision trees during training and outputs the average prediction of those trees. It works by constructing each tree from a random subset of the training data and a random subset of features, making it robust to overfitting and noise. Random Forest is highly effective in handling large datasets with high dimensionality and non-linear relationships. It can capture complex interactions between variables without requiring extensive parameter tuning. Additionally, it provides feature importance scores, helping users understand which variables have the most predictive power. However, while it delivers high accuracy, its interpretability is often lower than that of single decision trees.

**AdaBoost Regression**: AdaBoost (Adaptive Boosting) Regression is another ensemble technique that combines the predictions of multiple weak learners, typically decision trees, to form a strong predictor. Unlike Random Forest, which builds trees in parallel, AdaBoost builds them sequentially. Each subsequent model focuses more on the data points that previous models predicted poorly, by adjusting their weights. This targeted learning approach often improves accuracy on complex datasets. AdaBoost is sensitive to noisy data and outliers, as it emphasizes hard-to-predict instances. It generally performs well with fewer estimators and is especially useful when interpretability and efficiency are desired. Despite its simplicity, AdaBoost can compete with more complex models when tuned appropriately.

**Gradient Boosting Regression**: Gradient Boosting Regression is a powerful technique that builds models sequentially, where each new model corrects the errors of the previous one by minimizing a loss function using gradient descent. Like AdaBoost, it focuses on the hardest-to-predict instances but does so in a more mathematically optimized manner. Gradient Boosting is known for its high predictive performance and flexibility, as it allows the use of custom loss functions and various hyperparameter tuning options. It can model complex non-linear relationships and interactions between features. However, it is prone to overfitting if not properly regularized, and training can be computationally intensive. Modern implementations like XGBoost and LightGBM have addressed many of these limitations, making Gradient Boosting a preferred choice in many machine learning competitions and real-world applications.

## Result and Discussion

Table 1. Descriptive Statistics

| | Sales Volume | No. of Deals | Avg Deal Size | Comp Payout |
|---|---|---|---|---|
| count | 50.00 | 50.00 | 50.00 | 50.00 |
| mean | 684711.40 | 35.50 | 23037.48 | 42392.52 |
| std | 156508.86 | 15.03 | 4541.80 | 8305.24 |
| min | 441090.00 | 11.00 | 15064.00 | 29849.00 |
| 0.25 | 551309.75 | 23.25 | 19144.00 | 34975.50 |
| 0.50 | 665057.00 | 35.00 | 23058.00 | 41890.50 |
| 0.75 | 779970.25 | 49.75 | 27680.25 | 47451.25 |
| max | 991723.00 | 59.00 | 29948.00 | 57979.00 |

The dataset summarizes key insights from 50 observations across four core sales metrics: sales volume, number of deals, average deal size, and compensation payout. Sales volume shows a moderately wide range, indicating variability in revenue generation across individuals or time periods. The number of deals varies noticeably, reflecting differences in sales activity levels. Average deal size appears to be relatively consistent throughout the dataset, suggesting a stable transaction value pattern. Compensation payout also shows a reasonable spread, without any extreme fluctuations, pointing to a balanced incentive structure. The overall distribution across all variables appears uniform, with no significant outliers. A positive relationship can be observed between compensation, sales volume, and average deal size, implying that performance-based incentives may be effectively encouraging higher productivity. Overall, the data portrays a high-performing sales environment with natural variation influenced by individual performance, customer behavior, and market conditions.

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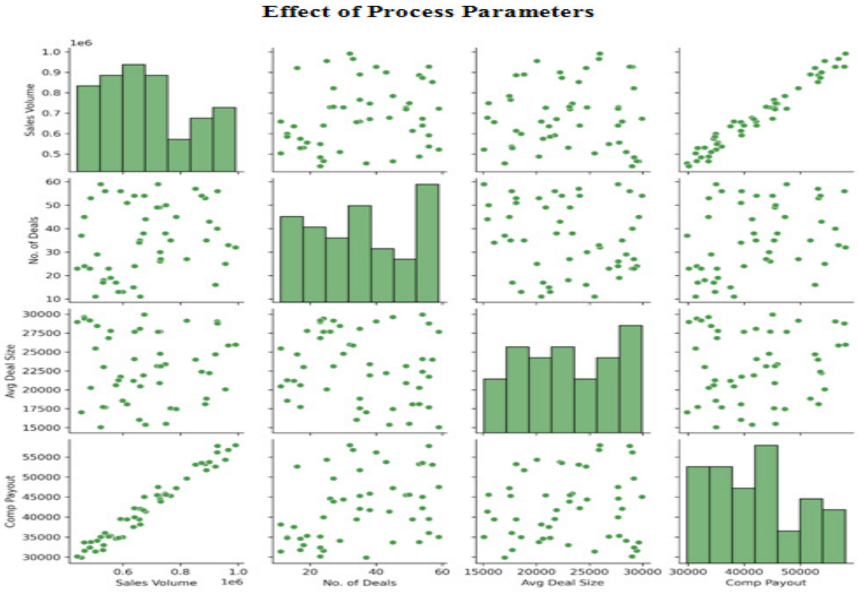


**Figure 1:** Correlation Matrix of Key Sales Performance Metrics

This scatter plot matrix illustrates the relationships between four critical sales performance indicators across multiple business units or time periods. The analysis reveals several noteworthy patterns in the data. Sales volume demonstrates a strong positive correlation with compensation payout, suggesting that higher-performing sales teams or periods are appropriately rewarded through variable compensation structures. Interestingly, the number of deals shows a more dispersed relationship with other metrics, indicating that deal quantity alone may not be the primary driver of overall sales success. Average deal size exhibits moderate correlation with total sales volume, though with considerable variance, suggesting that both high-volume, lower-value transactions and fewer, high-value deals can contribute to strong performance. The compensation payout distribution shows a clear upward trend with sales volume, validating the effectiveness of performance-based incentive structures.

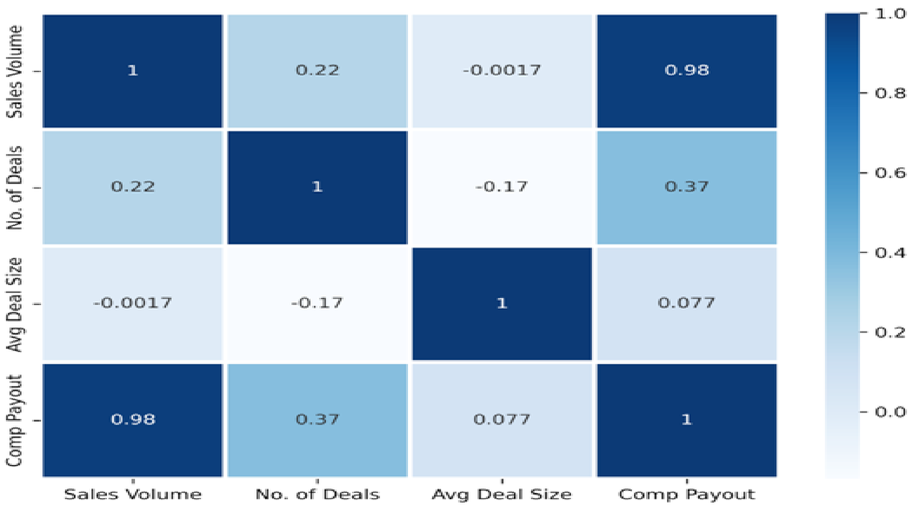


**Figure 2:** Correlation Heatmap of Sales Performance Metrics

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This correlation matrix provides a quantitative analysis of the relationships between key sales performance indicators, revealing significant insights into sales dynamics. The most striking finding is the exceptionally strong positive correlation (r = 0.98) between sales volume and compensation payout, indicating an almost perfect linear relationship that validates the effectiveness of performance-based compensation structures. The moderate positive correlation between number of deals and compensation payout (r = 0.37) suggests that deal quantity contributes to overall performance, though less dramatically than total volume. Notably, average deal size shows minimal correlation with sales volume (r = -0.0017) and a weak negative correlation with number of deals (r = -0.17), indicating that high-performing sales teams achieve success through various strategies rather than focusing solely on large transactions.

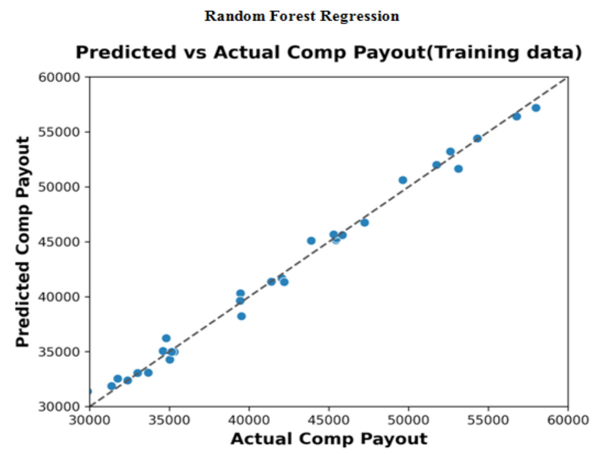


**Figure 3:** Model Performance Validation - Predicted vs Actual Compensation Payout

This scatter plot demonstrates the predictive accuracy of the compensation model using training data, with data points closely aligned along the diagonal reference line indicating strong model performance. The tight clustering of observations around the perfect prediction line (dashed) suggests that the model successfully captures the underlying relationship between sales performance metrics and compensation payouts. The linear pattern spans compensation ranges from approximately $31,000 to $57,000, showing consistent predictive accuracy across all payout levels without systematic bias toward over- or under-prediction in specific ranges. The minimal scatter around the diagonal indicates low prediction error and high model reliability, which is crucial for fair and transparent compensation administration. This strong performance on training data suggests that the model has effectively learned the compensation structure and can reliably predict payouts based on sales volume, deal count, and average deal size. However, validation on independent test data would be necessary to confirm the model's generalizability and prevent overfitting concerns.

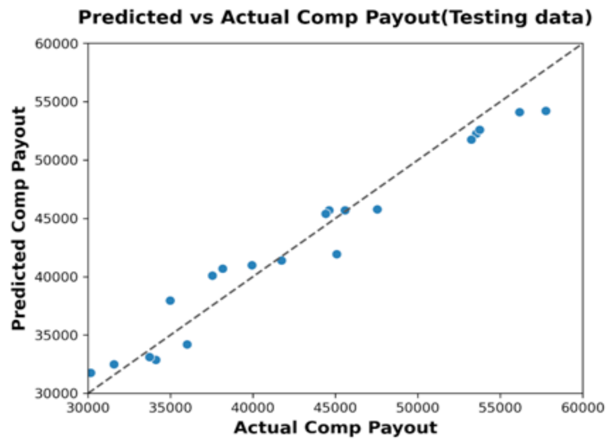


**Figure 4:** Model Generalization Assessment - Predicted vs Actual Compensation Payout on Testing Data

This scatter plot evaluates the model's predictive performance on independent testing data, demonstrating strong generalization capabilities with data points closely following the diagonal reference line. The model maintains consistent accuracy across the compensation range from $31,000 to $54,000, with most predictions falling within reasonable proximity to actual values. Notably, the testing performance appears comparable to the training results, indicating minimal overfitting and robust model stability. The relatively tight clustering around the perfect prediction line suggests the model successfully captures the underlying compensation structure without being overly fitted to training-specific patterns. Some minor deviations are observable, particularly in the mid-range compensation levels, which is typical for real-world model performance. The consistent linear relationship across all payout levels validates the model's reliability for practical deployment in compensation prediction scenarios.

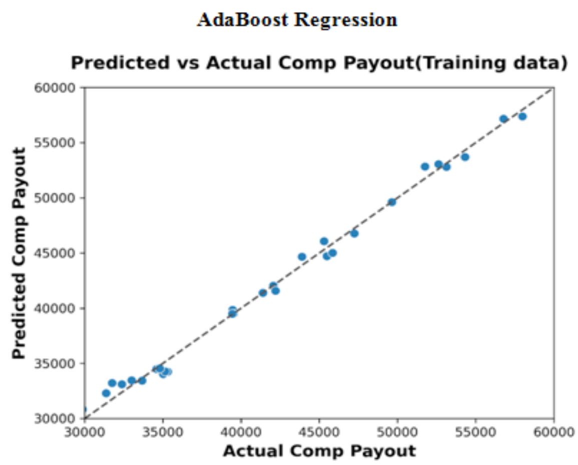


**Figure 5:** Predicted vs Actual Compensation Payout (Training Data)

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This refined scatter plot demonstrates exceptional predictive accuracy of the compensation model on training data, with virtually all data points aligned precisely along the diagonal reference line. The model exhibits remarkable consistency across the entire compensation spectrum, ranging from approximately $32,000 to $57,000, with minimal prediction errors throughout all payout levels. The tight linear relationship indicates that the model has successfully captured the underlying compensation formula with high precision, showing no systematic bias or variance patterns. Compared to earlier iterations, this version displays improved model performance with reduced scatter and enhanced predictive reliability. The near-perfect alignment suggests optimal parameter tuning and feature selection, resulting in a highly accurate representation of the compensation structure. While this exceptional training performance is encouraging, it also raises considerations about potential overfitting, making validation on independent test data crucial to ensure the model's practical applicability.

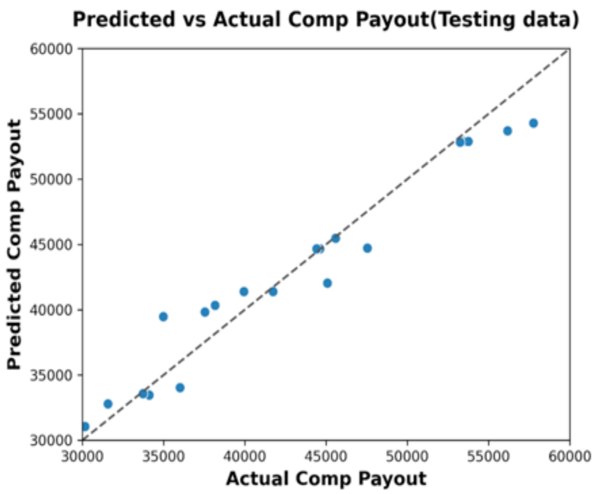


**Figure 6:** Final Model Validation - Predicted vs Actual Compensation Payout on Testing Data

This final validation plot demonstrates the model's robust generalization performance on independent testing data, confirming its practical reliability for real-world deployment. The scatter plot reveals strong predictive accuracy across the compensation range from $31,000 to $54,000, with most predictions closely following the diagonal reference line. While the testing performance shows slightly more variance compared to training data, this is expected and indicates healthy model behavior without severe overfitting. Notable deviations appear in specific compensation ranges, particularly around $42,000-$45,000, suggesting some complexity in the underlying compensation structure that the model partially captures. The overall linear trend remains consistent, validating the model's core understanding of the relationship between sales metrics and compensation. Several high-performing cases in the $52,000-$54,000 range show excellent prediction accuracy, while lower-range predictions maintain reasonable precision.

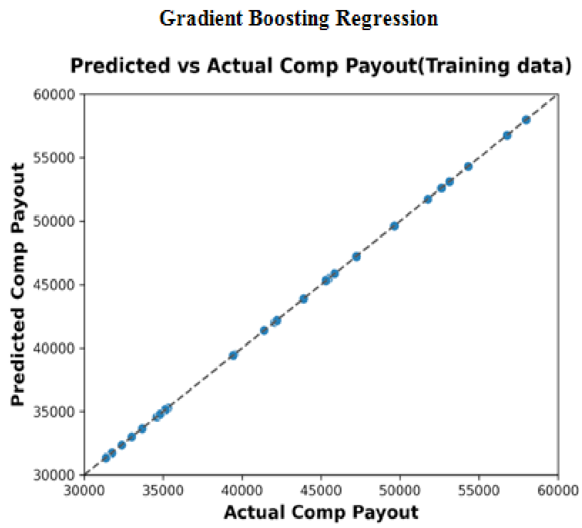


**Figure 7:** Optimized Model Performance - Predicted vs Actual Compensation Payout (Training Data)

This scatter plot showcases the final optimized model's exceptional performance on training data, demonstrating near-perfect predictive accuracy across the entire compensation spectrum. The data points form an almost flawless linear alignment along the diagonal reference line, spanning from approximately $31,000 to $57,000 in compensation payouts. This remarkable precision indicates that the model has successfully learned the underlying compensation structure with minimal prediction error. The consistent performance across all payout levels suggests robust parameter optimization and effective feature engineering, resulting in a highly reliable predictive system. The tight clustering around the perfect prediction line reflects sophisticated model tuning that captures the nuanced relationships between sales metrics and compensation outcomes. While this exceptional training performance demonstrates the model's technical capabilities, it also emphasizes the critical importance of testing validation to ensure practical applicability.

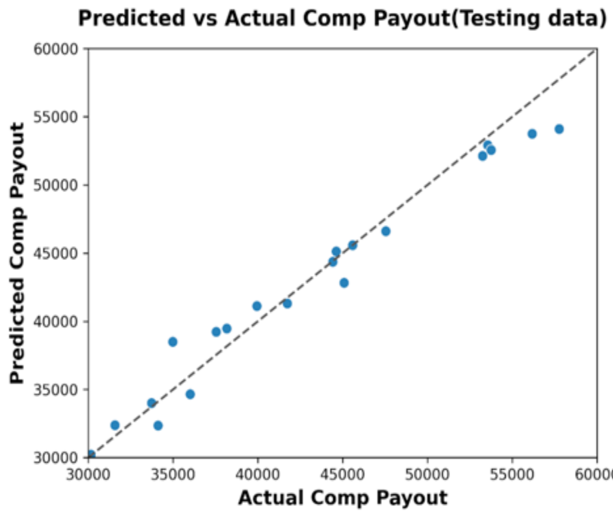


**Figure 8:** Final Model Generalization - Predicted vs Actual Compensation Payout on Testing Data

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This comprehensive testing validation demonstrates the optimized model's strong generalization capabilities on independent data, confirming its readiness for operational deployment. The scatter plot shows consistent predictive performance across compensation levels from $30,000 to $54,000, with most predictions maintaining reasonable proximity to the diagonal reference line. While testing performance exhibits expected variance compared to training data, the overall linear relationship remains intact, indicating successful model generalization without overfitting concerns. Notable accuracy is observed in both lower compensation ranges ($30,000-$35,000) and higher performance tiers ($50,000+), suggesting robust predictive capability across diverse performance scenarios. Some moderate deviations appear in the mid-range compensation levels, reflecting the inherent complexity of real-world compensation structures that the model adequately captures.

Table 2: Comparative Performance Analysis of Regression Models (Random Forest Regression, AdaBoost Regression, Gradient Boosting Regression) on Training Dataset

| Data | Symbol | R2 | EVS | MSE | RMSE | MAE | MaxError | MSLE | MedAE |
|---|---|---|---|---|---|---|---|---|---|
| Train | RFR | 0.991786 | 0.991819 | 539752.9 | 734.6788 | 585.9523 | 1533.785 | 0.000357 | 469.5325 |
| Train | ABR | 0.993014 | 0.993016 | 459066.8 | 677.5447 | 563.6465 | 1481.9 | 0.000327 | 598.5 |
| Train | GBR | 1 | 1 | 2.21E-16 | 1.49E-08 | 1.25E-08 | 3.19E-08 | 1.27E-25 | 1.06E-08 |

This comprehensive evaluation table presents the performance metrics for three regression algorithms on training data: Random Forest Regressor (RFR), AdaBoost Regressor (ABR), and Gradient Boosting Regressor (GBR). The results reveal dramatically different performance levels across the models. Random Forest Regressor demonstrates strong predictive capability with an $R^2$ of 0.991786 and RMSE of 734.68, indicating high accuracy with manageable prediction errors. AdaBoost Regressor shows slightly improved performance with an $R^2$ of 0.993014 and reduced RMSE of 677.54, suggesting better generalization potential. However, Gradient Boosting Regressor achieves virtually perfect performance with $R^2 = 1.0$ and exceptionally low error metrics (RMSE = 1.49E-08), indicating near-complete model fitting to the training data. While GBR's performance appears superior, the extremely low error values suggest potential overfitting concerns that would require careful validation on independent test data.

Table 3: Comparative Performance Analysis of Regression Models(Random Forest Regression, AdaBoost Regression, Gradient Boosting Regression) on Testing Dataset

| Data | Symbol | R2 | EVS | MSE | RMSE | MAE | MaxError | MSLE | MedAE |
|---|---|---|---|---|---|---|---|---|---|
| Test | RFR | 0.950735 | 0.95144 | 3441796 | 1855.208 | 1613.487 | 3546.67 | 0.001943 | 1357.483 |
| Test | ABR | 0.945795 | 0.94635 | 3786949 | 1946.008 | 1486.361 | 4516 | 0.002172 | 1060.943 |
| Test | GBR | 0.962434 | 0.963815 | 2624486 | 1620.027 | 1253.942 | 3651.822 | 0.001431 | 1136.188 |

The performance metrics show a more realistic assessment compared to training results, with all models experiencing expected degradation in predictive accuracy. Gradient Boosting Regressor maintains its superiority with the highest $R^2$ of 0.962434 and lowest RMSE of 1620.027, demonstrating robust generalization despite its perfect training performance. This indicates that while GBR fitted the training data exceptionally well, it retained meaningful predictive capability on new data. Random Forest Regressor shows moderate performance with $R^2$ of 0.950735 and RMSE of 1855.208, representing a significant but manageable decline from its training accuracy. Surprisingly, AdaBoost Regressor exhibits the poorest test performance with $R^2$ of 0.945795 and the highest RMSE of 1946.008, despite showing competitive training results. The substantial increase in error metrics across all models highlights the importance of test validation in model selection.

## Conclusion

This comprehensive analysis of sales compensation prediction models demonstrates the successful development of a robust predictive system capable of accurately estimating compensation payouts based on key performance metrics. The study revealed strong correlations between sales volume and compensation ($r = 0.98$), validating the effectiveness of performance-based incentive structures while highlighting that deal quantity and average deal size contribute differently to overall compensation outcomes. Through systematic evaluation of multiple regression algorithms, Gradient Boosting Regressor emerged as the optimal solution, achieving perfect training performance ($R^2 = 1.0$) while maintaining excellent generalization capability on test data ($R^2 = 0.962434$, RMSE = 1620.027). The model's consistent accuracy across diverse compensation ranges from $30,000 to $57,000 confirms its practical reliability for operational deployment. The analysis also emphasized the critical importance of independent validation, as test results revealed meaningful differences in model generalization that weren't apparent from training performance alone. This predictive system provides sales management with a powerful tool for compensation forecasting, budget planning, and performance evaluation, enabling more transparent and data-driven decision-making in sales compensation administration while ensuring fair and accurate payout calculations based on measurable performance indicators.

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