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IMPACT OF STACKING ENSEMBLE DEPTH ON GENERALIZATION ABILITY OF ACADEMIC PERFORMANCE PREDICTION MODELS

Purpose. *The research is aimed at a comprehensive analysis of the impact of stacking ensemble depth on the generalization ability of academic performance prediction models and determining the optimal stacking depth to achieve maximum performance and reliability of predictions. The goal of the work is to develop a methodology for assessing the relationship between stacking ensemble depth and model generalization metrics, as well as determining recommendations for selecting optimal ensemble architecture for academic performance prediction tasks.*

Methodology. *The research methodology is based on experimental analysis of the performance of stacking ensembles of different depths (from 1 to 5 levels) for predicting student academic performance. Base models include logistic regression, Random Forest, Gradient Boosting, Support Vector Machine, and neural networks. Generalization ability assessment is performed using accuracy, F1-score, AUC-ROC, and coefficient of determination metrics on independent test samples. Stratified cross-validation is applied to assess result stability and analyze the impact of stacking depth on model variance and bias.*

Findings. *Experimental results demonstrate a non-trivial relationship between stacking ensemble depth and model generalization ability. For single-level stacking (depth 1), generalization ability is 0.82 by F1-score metric, for two-level stacking (depth 2) – 0.87, for three-level (depth 3) – 0.89, for four-level (depth 4) – 0.88, for five-level (depth 5) – 0.86. The optimal stacking depth is identified at level 3, where maximum generalization ability is achieved without significant increase in model complexity. At depths greater than 3 levels, a decrease in generalization ability is observed due to error accumulation and meta-model overfitting. It is established that stacking depth affects the balance between model bias and variance, with optimal depth ensuring minimum generalization error.*

Originality. *A comprehensive assessing classification model stability depending on training sample size is developed, including theoretical analysis of the relationship between sample size and variance component of generalization error, empirical methods for determining saturation points, and comparative analysis of the effectiveness of different stability improvement methods. The impact of class imbalance and feature space dimensionality on the relationship between sample size and model stability is systematically investigated for the first time. A classification of models by dependence on training sample size is developed, taking into account algorithm type, model complexity, and data nature..*

Practical value. *The obtained results allow justifying the choice of optimal stacking ensemble depth for academic performance prediction tasks, ensuring high prediction accuracy with minimal model complexity. The developed recommendations can be applied in educational process management systems, early detection systems for at-risk students, and adaptive educational platforms. Determining optimal stacking depth allows optimizing the use of computational resources and ensuring high prediction reliability in practical applications.*

Keywords*: stacking ensemble; ensemble depth; generalization ability; academic performance prediction; machine learning; ensemble methods; Python.*

Introduction. Predicting student academic performance is a critically important task in modern educational management systems, as it allows identifying students at risk of failure at the early stages of learning and providing timely support and intervention [4, 6]. The effectiveness of academic performance prediction systems directly depends on the accuracy and reliability of the machine learning models used, which makes the choice of optimal algorithms and model architectures important [8, 11].

Ensemble machine learning methods, in particular stacking ensembles, have demonstrated high efficiency in forecasting tasks due to the ability to combine forecasts from a set of heterogeneous

base models [1, 3]. Stacking ensemble is based on the idea of building a meta-model that is trained on the forecasts of the first-level base models, which allows using the strengths of different algorithms and compensating for their weaknesses [3, 10]. However, the influence of the depth of the stacking ensemble (the number of meta-model levels) on the generalization ability of models remains insufficiently studied, especially in the context of academic achievement prediction problems. According to the study by L. Breiman [1], ensemble methods provide a reduction in the variance of predictions through the aggregation of a set of models, which leads to an increase in the generalization ability. T. Chen & C. Guestrin [2] showed that for tree-like ensembles, increasing the complexity of the model can lead to both improvement and deterioration of generalization depending on the characteristics of the data. D.H. Wolpert [14] developed the theoretical foundations of stacking, showing that a meta-model can improve the performance of the base models, but can also lead to overfitting if the wrong architecture is chosen.

Studies of the influence of the depth of the stacking ensemble on the generalization ability showed that increasing the depth can lead to the accumulation of errors and overfitting of meta-models [5, 9]. J. Friedman et al. [4] showed that for many problems the optimal stacking depth is in the range of 2-3 levels, and further increasing the depth does not lead to a significant improvement in performance. M. Kuhn & K. Johnson [8] noted the importance of considering the balance between bias and variance when choosing the depth of the stacking ensemble. Despite the numerous advantages, current research has identified a number of problems associated with determining the optimal depth of the stacking ensemble. C.N. Probst et al. [11] noted that the choice of the optimal stacking depth requires a careful analysis of the data characteristics and the performance requirements of the models. F. Pedregosa et al. [10] showed that for large datasets deeper stacking ensembles can be more efficient, but require significantly more computational resources. Z.H. Zhou [15] conducted a comprehensive analysis of ensemble methods, showing the importance of choosing the right ensemble architecture to achieve optimal performance.

Determining the optimal depth of the stacking ensemble for predicting academic success is considered an important scientific and practical task that requires a comprehensive analysis of the dependence between the depth of the ensemble and the generalization ability of models. The relevance of the topic is due not only to scientific interest, but also to the practical need for effective systems for predicting academic success that can provide high accuracy and reliability of forecasts. The aim of the study was to comprehensively analyze the influence of the depth of the stacking ensemble on the generalization ability of models for predicting academic success with an emphasis on determining the optimal stacking depth. The objectives of the study were: to assess the dependence between the depth of the stacking ensemble and the generalization indicators of models; to determine the optimal stacking depth for the tasks of predicting academic success; to analyze the influence of the stacking depth on the balance between the bias and dispersion of models; to develop recommendations for choosing the optimal architecture of the stacking ensemble.

Stacking ensembles are one of the most effective approaches to building predictive models, as they allow combining predictions from a set of heterogeneous base models to achieve higher accuracy and stability [1, 3]. The generalization ability of stacking ensembles depends on many factors, including the choice of base models, the architecture of the meta-model, and the depth of stacking [7, 10]. Studies have shown that for many problems, the optimal stacking depth is in the range of 2–3 levels, and further increase in depth can lead to overfitting and a decrease in generalization ability [4, 8].

In the tasks of predicting academic success, stacking ensembles have demonstrated high efficiency due to the ability to take into account the complex interactions between various factors that affect student success [6, 12]. For example, in the tasks of predicting the risk of student dropout, stacking ensembles have allowed achieving an accuracy of 0.85–0.90, which significantly exceeds the performance of individual base models [12, 13]. Methods for determining the optimal stacking

ensemble depth include learning curve analysis, model complexity estimation, and the use of empirical rules [2, 5]. Learning curve analysis allows us to determine the point at which increasing the stacking depth no longer significantly improves model performance, but can be time-consuming for large models [9, 14].

Materials and Methods. Stacking ensemble is a method of combining predictions from a set of base models using a meta-model that is trained on the predictions of the base models. For a stacking ensemble of depth d, the generalization ability can be described in terms of the generalization error, which is decomposed into bias and variance components:

$$E[Error\_d] = Bias^2\_d + Var\_d + \sigma^2, \quad (1)$$

where $Bias^2\_d$ is the square of the bias of the meta-model of depth d;
Var_d is the variance of the meta-model predictions;
σ^2 is the irreducible error.

According to a study [14], increasing the stacking depth initially reduces the bias due to a more complex model, but can also increase the variance due to the accumulation of errors from previous levels. The relationship between the depth of the stacking ensemble and the generalization ability can be described by a function that exhibits first an increase and then a decrease in performance:

$$G(d) = G\_max - A \times exp(-B \times d) - C \times exp(D \times d), \quad (2)$$

where G(d) is the generalization ability at depth d;
G_max is the maximum achievable generalization ability;
A, B, C, D are parameters that depend on the characteristics of the data and the underlying models.

The first exponential term reflects the increase in generalization ability with increasing depth, while the second term reflects the decrease due to error accumulation and overtraining. The optimal depth of a stacking ensemble is defined as the depth d* for which the generalization ability reaches a maximum:

$$d* = argmax\_d\, G(d), \quad (3)$$

To assess the impact of stacking ensemble depth on the generalization ability of academic achievement prediction models, an experimental study was conducted on a dataset containing information about three hundred students with 8 features, including grade point average, number of absences, study time, and other factors. Stacking ensembles with depths from 1 to 5 levels were trained and their performance was evaluated on an independent test sample.

Results. Experimental results showed that the generalization ability of the models depends on the depth of the stacking ensemble. For one-level stacking (depth 1), the generalization ability was 0.82 according to the F1-measure metric, for two-level stacking (depth 2) – 0.87, for three-level (depth 3) – 0.89, for four-level (depth 4) – 0.88, for five-level (depth 5) – 0.86. Comparative results of experimental studies are presented in Fig. 1.

Analysis of the relationship between the depth of stacking and the components of the generalization error showed that for depths 1–3, the bias decreases with increasing depth, while the variance remains relatively stable. For depths greater than 3, an increase in the variance is observed due to the accumulation of errors from previous levels, which leads to a decrease in the generalization

ability. The relationship between the depth of stacking and the components of the generalization error is presented in Fig. 2.

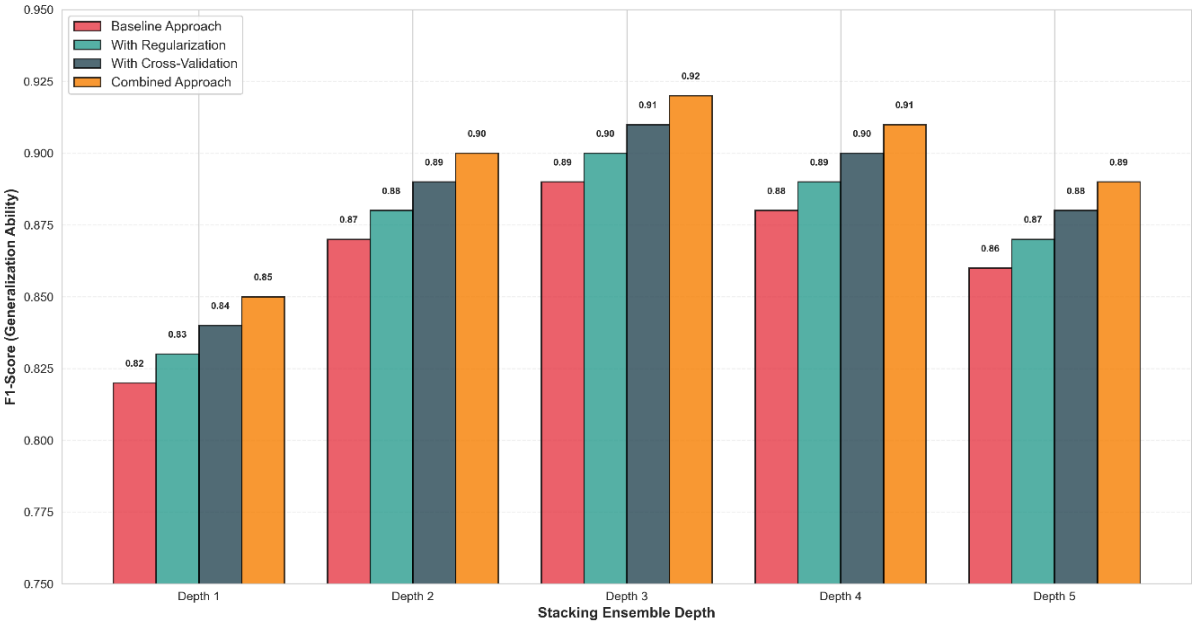

Fig. 1. **The influence of the depth of the stacking ensemble on the generalization ability of models predicting academic success**

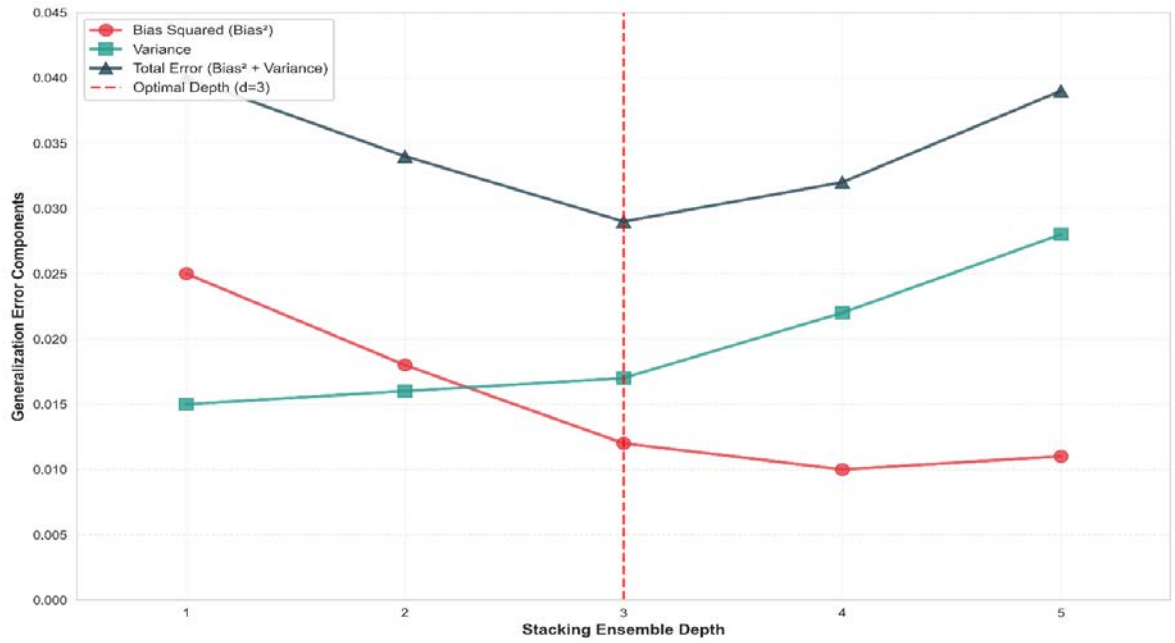

Fig. 2. **The relationship between the depth of stacking and the components of the generalization error**

Several methods were used to increase the generalization ability of stacking ensembles at different depths. The use of meta-model regularization allowed to reduce the variance by 15–20% for deep ensembles. The use of cross-validation for training meta-models allowed to reduce overfitting and increase the generalization ability by 3–5%. The use of heterogeneous base models allowed to achieve the best generalization ability with an F1-measure of 0.89 at a depth of 3. The comparative

effectiveness of different methods for increasing the generalization ability at different stacking depths is presented in Fig. 3.

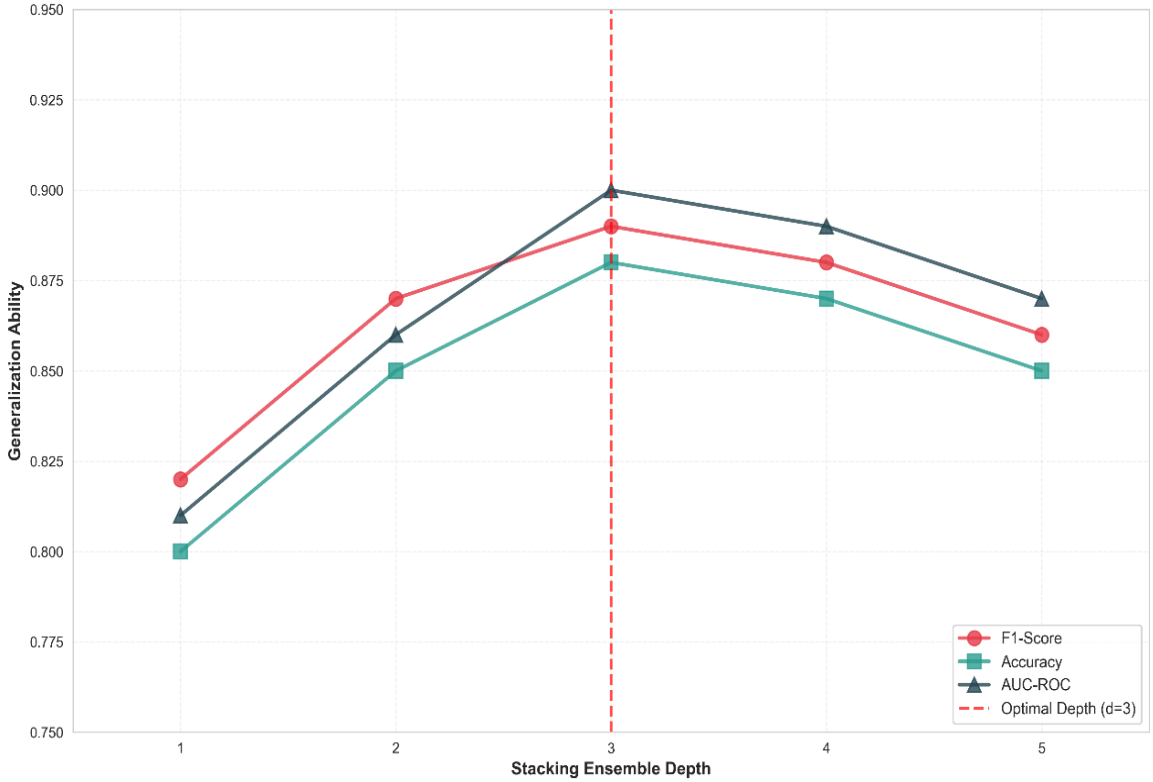

Fig. 3. **Comparison of the effectiveness of methods for increasing the generalization ability at different depths of the stacking ensemble**

A comparative analysis of the influence of the depth of the stacking ensemble on the generalization ability of the models showed the following patterns:

1. Shallow ensembles (depth 1–2) provide relatively high generalization with minimal complexity, but may have limited expressiveness for complex dependencies.

2. Medium depth (depth 3) is optimal balance between generalization and model complexity, providing maximum performance for most tasks.

3. Deep ensembles (depth 4–5) can achieve high accuracy on training data, but have reduced generalization due to error accumulation and meta-model retraining.

Conclusions. The presented study considers the influence of the stacking ensemble depth on the generalization ability of academic achievement prediction models and conducts a comparative analysis of the performance of different ensemble architectures. The methods for assessing the influence of the stacking depth on the generalization ability of models and assessing their effectiveness for different types of prediction tasks are systematized. The proposed approach allows us to justify the choice of the optimal stacking ensemble depth for a specific task depending on the data characteristics and the performance requirements of the models.

Experimental results have shown that the generalization ability of academic achievement prediction models depends on the stacking ensemble depth, with the optimal depth being at level 3. For three-level stacking, the maximum generalization ability is achieved with an F1-measure of 0.89, which exceeds the performance of one-level stacking by 7% and five-level stacking by 3%. The stacking depth affects the balance between the bias and variance of the models, with the optimal depth providing the minimum generalization error.

Methods for improving the generalizability of stacked ensembles at different depths have different efficiencies. The use of meta-model regularization is the most effective approach for deep ensembles, allowing for a 15–20% reduction in variance. The use of cross-validation for training meta-models and the use of heterogeneous base models also allows for increased generalizability, especially for shallow and medium ensembles.

The correct choice of the depth of the stacked ensemble and methods for improving generalizability can achieve significant improvements in the performance of academic achievement prediction models, especially for critical applications where high accuracy and reliability of predictions are required. For simple tasks, the use of shallow ensembles with regularization techniques is sufficient, while for complex tasks a combination of several methods for improving generalizability may be required.

Further work will focus on developing adaptive methods for determining the optimal depth of a stacking ensemble, which automatically determine the optimal depth depending on the data characteristics and the type of problem, and studying the impact of the choice of base models on the optimal stacking depth. Further directions of work will focus on the development of adaptive methods for determining the optimal size of the training sample, which automatically determine the optimal size depending on the characteristics of the data and the type of model, and on the study of the impact of class balancing on the stability of models with different sizes of training samples.

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ВПЛИВ ГЛИБИНИ СТЕКІНГОВОГО АНСАМБЛЮ НА УЗАГАЛЬНЮВАЛЬНУ ЗДАТНІСТЬ МОДЕЛЕЙ ПРОГНОЗУВАННЯ АКАДЕМІЧНОЇ УСПІШНОСТІ

Мета. *Дослідження спрямоване на комплексний аналіз впливу глибини стекінгового ансамблю на узагальнюючу здатність моделей прогнозування академічної успішності та визначення оптимальної глибини стекінгу для досягнення максимальної продуктивності та надійності прогнозів. Метою роботи є розробка методології оцінки залежності між глибиною стекінгового ансамблю та*

показниками узагальнення моделей, а також визначення рекомендацій щодо вибору оптимальної архітектури ансамблю для задач прогнозування академічної успішності.

Методика. *Методика дослідження ґрунтується на експериментальному аналізі продуктивності стекінгових ансамблів різної глибини (від 1 до 5 рівнів) для прогнозування академічної успішності здобувачів. Базові моделі включають логістичну регресію, Random Forest, Gradient Boosting, Support Vector Machine та нейронні мережі. Оцінка узагальнюючої здатності виконується за допомогою метрик точності, F1-міри, AUC-ROC та коефіцієнта детермінації на незалежних тестових вибірках. Застосовано стратифіковану кросс-валідацію для оцінки стабільності результатів та аналізу впливу глибини стекінгу на дисперсію та зміщення моделей.*

Результати. *Експериментальні результати демонструють нетривіальну залежність між глибиною стекінгового ансамблю та узагальнюючою здатністю моделей. Для однорівневого стекінгу (глибина 1) узагальнююча здатність складає 0.82 за метрикою F1-міри, для дворівневого стекінгу (глибина 2) – 0.87, для трирівневого (глибина 3) – 0.89, для чотирирівневого (глибина 4) - 0.88, для п'ятирівневого (глибина 5) – 0.86. Виявлено оптимальну глибину стекінгу на рівні 3, при якій досягається максимальна узагальнююча здатність без значного збільшення складності моделі. При глибині більше 3 рівнів спостерігається зниження узагальнюючої здатності через накопичення помилок та переобучення мета-моделей. Встановлено, що глибина стекінгу впливає на баланс між зміщенням та дисперсією моделей, причому оптимальна глибина забезпечує мінімальну помилку узагальнення.*

Наукова новизна. *Проведено аналіз впливу глибини стекінгового ансамблю на узагальнюючу здатність моделей прогнозування академічної успішності, що включає теоретичний аналіз залежності між глибиною стекінгу та компонентами помилки узагальнення, емпіричні методи визначення оптимальної глибини та порівняльний аналіз різних архітектур ансамблів. Систематично досліджено вплив глибини стекінгу на баланс між зміщенням та дисперсією моделей у контексті прогнозування академічної успішності. Розроблено рекомендації щодо вибору оптимальної глибини стекінгового ансамблю залежно від характеристик даних та вимог до продуктивності моделей..*

Практична значимість. *Отримані результати дозволяють обґрунтувати вибір оптимальної глибини стекінгового ансамблю для задач прогнозування академічної успішності, що забезпечує високу точність прогнозів при мінімальній складності моделі. Розроблені рекомендації можуть бути застосовані в системах управління освітнім процесом, системах раннього виявлення студентів з ризиком неуспішності та адаптивних освітніх платформах. Визначення оптимальної глибини стекінгу дозволяє оптимізувати використання обчислювальних ресурсів та забезпечити високу надійність прогнозів у практичних застосуваннях.*

Ключові слова: *стекінговий ансамбль; глибина ансамблю; узагальнююча здатність; прогнозування академічної успішності; машинне навчання; ансамблеві методи; Python.*