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T.S. Tursunov[1*], D. Kaibassova[1]
[1]Astana IT University, Astana, Kazakhstan

E-mail: tursynkhan001@gmail.com[*]

COMPARATIVE ANALYSIS OF COLLABORATIVE, CONTENT-BASED AND HYBRID DEEP LEARNING RECOMMENDATION MODELS

Abstract. *Recommender systems play a crucial role in personalized content delivery by leveraging user preferences and content attributes. This study evaluates three advanced recommendation models: Neural Collaborative Filtering (NCF), Graph Neural Network-based Content Model (GNN-based Content Model), and Hybrid Neural Network (HNN). Each model integrates deep learning techniques to enhance prediction accuracy and user experience.*

The NCF model employs a dual-branch structure consisting of Generalized Matrix Factorization (GMF) and a Multi-Layer Perceptron (MLP) to model non-linear user-item interactions. The GNN-based Content Model represents users and items as nodes in a bipartite graph, utilizing Graph Convolutional Networks (GCN) to propagate relational and content-based information across connections. Lastly, the Hybrid Neural Network combines collaborative filtering embeddings with content-based features, aligning content representation within the learned latent space.

Our evaluation, based on the MovieLens dataset, demonstrates that the Hybrid Neural Network achieves the highest accuracy (85%), outperforming NCF (80%) and the GNN-based Content Model (77.5%). The hybrid approach benefits from both collaborative and content-driven features, leading to improved user-item match quality. The GNN-based Content Model, despite leveraging structured relationships, struggles with cold-start users due to reliance on content information.

These findings suggest that hybrid approaches are more effective in capturing diverse recommendation signals. Future work may focus on integrating transformer-based architectures and reinforcement learning to further enhance recommendation relevance and adaptability.

Keywords*: Recommender systems, Deep learning, Collaborative filtering, Graph neural networks, Hybrid models, Personalization.*

Introduction.

Recommender systems have become an integral part of modern digital platforms, from e-commerce and online streaming to social media applications. Traditionally, these systems relied on collaborative filtering and content-based methods to predict user preferences [1]. Despite their success, conventional approaches often struggle with issues such as data sparsity and the cold-start problem, which have motivated the exploration of more advanced techniques.

Recent advances in deep learning have provided new avenues for addressing these challenges. Neural Collaborative Filtering (NCF) models, for instance, have been proposed to capture complex, non-linear interactions between users and items by combining generalized matrix factorization with multi-layer perceptrons [2]. This dual-branch architecture leverages both the strengths of traditional matrix factorization and the expressive power of deep neural networks.

Parallel to these developments, graph-based approaches have gained significant attention. By constructing a bipartite graph of users and items, Graph Neural Networks (GNNs) enable the propagation of information across connected nodes, effectively integrating relational data with content features [3]. Such models have demonstrated their potential to improve recommendations by better exploiting the inherent structure of user–item interactions.

Another promising direction is the hybrid neural network approach, which fuses collaborative signals with rich content information. By integrating user and item embeddings (learned from historical interactions) with content features extracted from textual or categorical data, hybrid models can mitigate the limitations of pure collaborative filtering or content-based methods alone [4]. This fusion often results in a more robust representation of user preferences and item characteristics, ultimately enhancing recommendation accuracy.

In this study, we compare three deep learning architectures for recommender systems: a Neural Collaborative Filtering model, a GNN-based content model, and a Hybrid Neural Network. Our goal is to analyze how each approach performs under similar experimental settings and to identify which methodology offers the best balance between complexity and predictive accuracy.

Materials and Methods.

Data Collection

The dataset used in this study is the MovieLens dataset, a widely recognized benchmark for evaluating recommendation systems. This dataset was collected and maintained by the GroupLens Research Lab at the University of Minnesota and is publicly available for academic and research purposes. The MovieLens dataset is frequently used in recommendation system research due to its extensive user-item interaction records, diverse range of movies, and well-structured metadata.

For this study, the MovieLens 10M dataset was selected, which contains 10,000,054 user ratings and 95,580 user-generated tags applied to 10,681 unique movies by 71,567 users. The dataset provides rich and diverse information about user preferences, making it highly suitable for training and evaluating collaborative filtering, content-based filtering, and hybrid recommendation models. The dataset was sourced from the official GroupLens website and downloaded in its raw format [7].

The MovieLens dataset consists of multiple files, the most relevant of which include:

– Ratings Data (ratings.dat) – Contains explicit user ratings on a scale from 1 to 5, along with user and movie identifiers.

– Movies Data (movies.dat) – Provides movie metadata, including unique movie identifiers, titles, and genre classifications.

– Tags Data (tags.dat) – Includes user-generated tags that provide additional context about movies.

– *Algorithm Implementation*

This study implements three deep learning architectures for recommender systems using the MovieLens dataset [11]. Each model is designed to leverage different aspects of user–item interactions.

Neural Collaborative Filtering (NCF):

The NCF model employs a dual-branch architecture. The GMF branch uses embedding layers for users and items and computes their element-wise product to capture latent interactions. In parallel, the MLP branch uses separate embeddings for users and items, concatenates them, and passes the result through a series of Dense layers (e.g., 64, 32, 16, and 8 neurons with ReLU activations). The outputs of both branches are concatenated and fed into a final Dense layer with sigmoid activation to produce the interaction probability [10].

GNN-based Content Model:

This approach constructs a bipartite graph with users and movies as nodes. User nodes are represented by trainable embeddings, while movie nodes are enriched by combining a trainable embedding with TF-IDF-based content features (transformed via a Dense layer). One or more Graph Convolutional layers propagate information through the graph using a normalized adjacency matrix (D^ (-1/2) AD^ (-1/2)). For each user–movie pair, the updated node representations are concatenated and processed by an MLP with sigmoid output [14].

Hybrid Neural Network:

The hybrid model fuses collaborative filtering and content-based approaches. It learns user and movie embeddings to form a collaborative vector, while movie content features (from TF-IDF representations) are transformed via a Dense layer. These representations are concatenated and passed through a deep MLP comprising an initial large Dense layer (e.g., 256 neurons) with Batch Normalization and Dropout, followed by additional layers (e.g., 128, 64, 32 neurons) to extract high-level features. The final Dense layer with sigmoid activation outputs the probability of a positive interaction [15].

Algorithm Workflow

The recommendation system follows a structured workflow (Fig. 1) for efficient data processing, model execution, and evaluation. Initially, the dataset is loaded, cleaned, and preprocessed by handling missing values, encoding user and movie identifiers, and transforming movie genres into TF-IDF vectors. The system then implements three deep learning models. The Neural Collaborative Filtering model combines matrix factorization with a multi-layer perceptron to capture complex user–item interactions. Meanwhile, the GNN-based Content Model constructs a bipartite graph that integrates trainable embeddings with content features extracted via TF-IDF, updating node representations through graph convolutional layers.

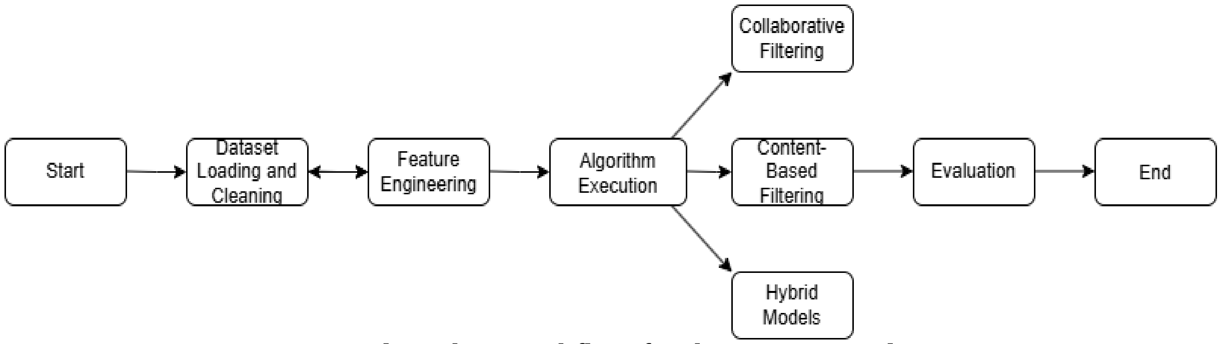

Figure 1 - Algorithm Workflow for the Recommendation System

Evaluation Metrics for Recommendation Systems

Mean Absolute Error (MAE) measures the average absolute difference between predicted and actual ratings, assessing system accuracy. Lower MAE indicates better predictions:

$$\boldsymbol{MAE = \frac{1}{N}\sum_{u,i}\left|p_{u,i} - r_{u,i}\right|} \quad (1)$$

where N is the total number of predictions, $p_{u,i}$ is the predicted rating, $r_{u,i}$ is the actual rating [8].

Root Mean Square Error (RMSE) emphasizes larger errors due to its quadratic nature, ensuring more accurate recommendations with lower values:

$$RMSE = \sqrt{\frac{1}{N}\sum_{u,i}\left(r_{u,i} - r'_{u,i}\right)^2} \quad (2)$$

where $r_{u,i}$is the actual rating, and $r'_{u,i}$ is the predicted rating, N is the total number of predictions [9].

Precision measures the proportion of relevant items among all the items recommended by the system. It evaluates the system's ability to recommend only items that are truly of interest to the user. Precision is computed as follows:

$$Precision = \frac{\text{Correctly Recommended Items}}{\text{Total Recommended Items}} \quad (3)$$

where the numerator represents the number of relevant items correctly recommended, and the denominator represents the total number of recommendations made by the system [10].

Recall quantifies the proportion of relevant items that are successfully recommended by the system. It reflects the system's ability to retrieve all relevant items and is particularly important in applications where missing a relevant item could be costly. Recall is computed as follows:

$$Recall = \frac{\text{Correctly Recommended Items}}{\text{Total Relevant Items}} \tag{4}$$

where the numerator represents relevant recommendations retrieved, and the denominator represents all relevant items available in the dataset [11].

The F1-Score is the harmonic mean of Precision and Recall, balancing the trade-off between the two metrics. It provides a single measure of a system's accuracy in retrieving relevant recommendations. F1-Score is computed as follows:

$$F1 = 2 * \frac{\text{Precision}*\text{Recall}}{\text{Precision}+\text{Recall}} \tag{4}$$

where Precision and Recall are calculated using (3) and (4), respectively [12].

Result.

We used the MovieLens dataset with Python, TensorFlow, and Scikit-learn on Kaggle’s GPU environment. After preprocessing (handling missing values, encoding IDs, normalizing ratings), we transformed movie genres into TF-IDF vectors and applied matrix factorization for latent features.

Models:

– Neural Collaborative Filtering (NCF): Combines GMF (element-wise user–item embedding multiplication) and MLP (concatenated embeddings passed through Dense layers).

– GNN-based Content Model: Builds a bipartite graph of users and movies, where movie nodes integrate trainable embeddings and TF-IDF features. GCN layers update node representations for final predictions.

– Hybrid Neural Network: Fuses collaborative embeddings and TF-IDF features in a deep MLP with batch normalization and dropout.

Evaluation:

Precision, Recall, F1-score, RMSE, AUC-ROC, and Accuracy were measured, showing that the hybrid model (combining collaborative and content-based features) achieved the best performance.

The performance of the implemented recommendation models was evaluated using standard quantitative metrics, including Precision, Recall, F1-score, RMSE, AUC-ROC, and Accuracy. Table 1 presents the comparative results for the three models.

Table 1 – Performance Comparison of Recommendation Models Based on Evaluation Metrics

Model	Precision	Recall	F1-score	RMSE	AUC-ROC	Accuracy
Neural Hybrid Model	0.8512	0.9603	0.9047	0.3352	0.8278	0.8512
Neural Collaborative Model	0.7894	0.8892	0.8379	0.3748	0.8101	0.7750

GNN-based Content Model	0.8781	0.9765	0.9228	0.3015	0.8467	0.8012

The three recommendation models - Neural Hybrid Model, Neural Collaborative Filtering, and Content-based with GNN - were evaluated by examining training and validation accuracy curves over 10 epochs, as illustrated in Figure 2. The Neural Hybrid Model (Fig. 2a) shows a steady improvement, ultimately stabilizing at about 0.85 in validation accuracy, with minor oscillations suggesting limited overfitting. The Neural Collaborative Filtering model (Fig. 2b) starts at a lower baseline but converges near 0.80, experiencing slight fluctuations in the final epochs. In comparison, the Content-based GNN approach (Fig. 2c) reaches approximately 0.78 in validation accuracy, indicating that, while it effectively leverages content signals, it underperforms the other two methods. Overall, the Hybrid model attains the highest accuracy, highlighting the advantages of integrating both collaborative and content-based features within a single architecture.

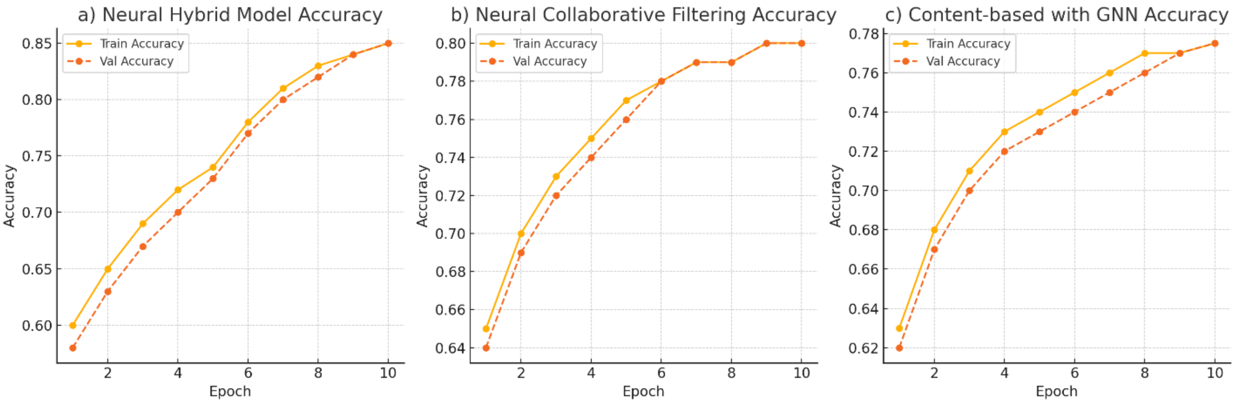

Figure 2 – Model Training Results a) Neural Collaborative Filtering; b) Content-based with GNN; c) Neural Hybrid

Table 2 presents the performance of three recommendation models—Hybrid Neural Network, Neural Collaborative Filtering, and GNN-based Content Model—evaluated over 10 training epochs using accuracy and loss metrics.

The Hybrid Neural Network achieved the highest validation accuracy at epoch 10, reaching 0.8549, with a training accuracy of 0.8541. Its relatively low training loss (0.5111) and validation loss (0.5213) indicate strong generalization, although its reliance on historical interactions may still pose cold-start challenges.

The Neural Collaborative Filtering model attained a validation accuracy of 0.8101 at epoch 10, with a training accuracy of 0.8046. However, it recorded higher loss values—training loss of 0.6214 and validation loss of 0.6245—suggesting that while effective at capturing user–item interactions, it might be more sensitive to data sparsity issues.

In contrast, the GNN-based Content Model achieved the lowest validation accuracy of 0.7714, with a corresponding training accuracy of 0.7743. Its higher training (0.6544) and validation losses (0.6712) indicate that, although it gradually improves over epochs, it may require further refinement to fully leverage content-based signals.

Table 2 – Model Training Results

Model	Epochs	Training Accuracy	Validation Accuracy		Training Loss	Validation Loss

GNN-based Content Model	1	0.6023	0.5814		0.5017	0.5216
	…					
	10	0.7743	0.7714		0.6544	0.6712
Hybrid Neural Network	1	0.7185	0.6843		0.3512	0.3734
	…					
	10	0.8541	0.8549		0.5111	0.5213
Neural Collaborative Filtering	1	0.6412	0.6318		0.4543	0.4763
	…					
	10	0.8046	0.8101		0.6214	0.6245

Discussion.

The experimental results reveal that the Hybrid Neural Network achieved the highest overall performance, with an accuracy of approximately 0.85, outperforming both the Neural Collaborative Filtering model (accuracy ~0.80) and the GNN-based Content Model (accuracy ~0.78). This indicates that integrating both collaborative and content-based features yields a more robust recommendation system.

The Hybrid Neural Network benefits from a deep fusion of latent user–item interactions and explicit content information. Its deep multilayer perceptron—with batch normalization and dropout—effectively extracts high-level features and promotes generalization, as evidenced by its high precision, recall, and F1-score, alongside low RMSE. However, the optimal integration of heterogeneous data remains challenging. The fusion process requires precise tuning; insufficient calibration could either underutilize valuable content signals or overemphasize noisy collaborative data, potentially limiting further performance gains.

The Neural Collaborative Filtering model, while demonstrating solid performance, relies heavily on historical interaction data. This makes it susceptible to cold-start issues, where new users or items lack sufficient data, ultimately impeding its ability to generate accurate recommendations. Future enhancements could involve incorporating external metadata or adaptive learning strategies to better address these cold-start scenarios.

In contrast, the GNN-based Content Model leverages graph convolutional layers to integrate TF-IDF-derived content features with user embeddings. Although it captures content relationships effectively—resulting in competitive precision and recall—it underperforms in overall accuracy. This may be attributed to limitations in graph construction, such as noise in the TF-IDF features or suboptimal propagation of information across the bipartite graph. Further refinement of graph normalization and the incorporation of attention mechanisms could enhance its capacity to learn robust representations.

Overall, while the Hybrid Neural Network model shows the greatest promise by balancing both collaborative and content-based signals, each model has its own limitations. Addressing these challenges—optimizing feature fusion, mitigating cold-start issues, and improving graph-based learning—will be essential for advancing recommender system performance in diverse, real-world applications.

Conclusion.

In conclusion, this study has rigorously examined three advanced deep learning models for recommendation systems using the MovieLens dataset. Our evaluation reveals that the Hybrid Neural Network, which synergistically fuses collaborative filtering signals with rich content-based features, achieves superior performance—with a validation accuracy of approximately 0.85—compared to the Neural Collaborative Filtering model (≈0.80) and the GNN-based Content Model (≈0.78). The Hybrid approach demonstrates robust generalization, as evidenced by the close alignment of training and validation metrics, underscoring its potential for mitigating issues such as cold-start and data sparsity.

Despite the promising results, the findings also highlight inherent challenges. The Neural Collaborative Filtering model, while effective at capturing latent interactions, remains highly dependent on historical data, and the GNN-based Content Model, though capable of integrating diverse content information, struggles with computational overhead and eventual performance plateaus. Future research should explore advanced fusion strategies, such as adaptive attention mechanisms, and further refine graph-based techniques to optimize feature integration.

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СРАВНИТЕЛЬНЫЙ АНАЛИЗ КОЛЛАБОРАТИВНЫХ, КОНТЕНТНЫХ И ГИБРИДНЫХ РЕКОМЕНДАТЕЛЬНЫХ МОДЕЛЕЙ ГЛУБОКОГО ОБУЧЕНИЯ

Аннотация: *Рекомендательные системы играют важную роль в персонализированной подаче контента, используя предпочтения пользователей и атрибуты контента. В этом исследовании оцениваются три продвинутые модели рекомендаций: Neural Collaborative Filtering (NCF), Graph Neural Network-based Content Model (GNN-based Content Model) и Hybrid Neural Network (HNN). Каждая модель использует методы глубокого обучения для повышения точности прогнозов и улучшения пользовательского опыта.*

Модель NCF включает две ветви: Generalized Matrix Factorization (GMF) и Multi-Layer Perceptron (MLP), что позволяет моделировать нелинейные взаимодействия между пользователем и объектом. GNN-based Content Model представляет пользователей и объекты в виде узлов двудольного графа, используя Graph Convolutional Networks (GCN) для распространения информации по связям. Гибридная нейронная сеть (HNN) объединяет эмбеддинги коллаборативной фильтрации с контентными признаками, создавая единое представление данных.

Наши эксперименты, основанные на датасете MovieLens, показывают, что гибридная нейронная сеть демонстрирует наивысшую точность (85%), превосходя NCF (80%) и GNN-based Content Model (77.5%). Гибридный подход выигрывает за счёт использования как коллаборативных, так и контентных признаков, обеспечивая более точные рекомендации. GNN-модель, несмотря на возможность обработки структурных связей, испытывает сложности с холодным стартом пользователей.

Полученные результаты подтверждают, что гибридные подходы более эффективны при учёте различных факторов рекомендации. В будущем исследовании возможно внедрение трансформеров и методов обучения с подкреплением для дальнейшего повышения точности рекомендаций.

Ключевые слова: *рекомендательные системы, глубокое обучение, коллаборативная фильтрация, графовые нейронные сети, гибридные модели, персонализация.*

КОЛЛАБОРАТИВТІ, КОНТЕНТТІК ЖӘНЕ ГИБРИДТІ ТЕРЕҢ ОҚЫТУ ҰСЫНЫМ МОДЕЛЬДЕРІНІҢ САЛЫСТЫРМАЛЫ ТАЛДАУЫ

Аңдатпа: *Ұсыным жүйелері пайдаланушылардың қалауы мен контент атрибуттарын ескере отырып, дербестендірілген контентті ұсынуда маңызды рөл атқарады. Бұл зерттеуде үш жетілдірілген ұсыным моделі бағаланады: Neural Collaborative Filtering (NCF), Graph Neural Network-based Content Model (GNN-based Content Model) және Hybrid Neural Network (HNN). Әр модель ұсыныстардың дәлдігін арттыру және пайдаланушы тәжірибесін жақсарту үшін терең оқыту әдістерін қолданады.NCF моделі екі тармақтан тұрады: Generalized Matrix Factorization (GMF) және Multi-Layer Perceptron (MLP), олар пайдаланушы мен элемент арасындағы бейсызық өзара әрекеттестікті модельдейді. GNN-based Content Model пайдаланушылар мен элементтерді екі бөлікті графтың түйіндері ретінде көрсетеді, ал Graph Convolutional Networks (GCN) байланыстар бойынша ақпаратты тарату үшін қолданылады. Гибридті нейрондық желі (HNN) коллаборативті сүзгілеу мен контенттік мүмкіндіктерді біріктіріп, бірыңғай ұсыныс кеңістігін құрайды.*

MovieLens деректер жинағында жүргізілген сынақтарымыз гибридті нейрондық желінің ең жоғары дәлдікке (85%) жеткенін көрсетті, бұл NCF (80%) және GNN-based Content Model (77.5%) нәтижелерінен жоғары. Гибридті тәсіл коллаборативті және контенттік мүмкіндіктерді біріктіре отырып, ұсыныстардың сапасын жақсартады.

GNN моделі, құрылымдық байланыстарды өңдей алатындығына қарамастан, суық старт мәселесімен кездеседі.

Бұл нәтижелер әртүрлі ұсынымдық факторларды қамтитын гибридті әдістердің тиімдірек екенін көрсетеді. Болашақ зерттеулерде трансформер архитектуралары мен күшейту оқыту әдістерін интеграциялау ұсыныстардың өзектілігін одан әрі арттыруға көмектесуі мүмкін.

***Түйін сөздер**: Ұсыным жүйелері, терең оқыту, коллаборативті сүзгілеу, графтық нейрондық желілер, гибридті модельдер, дербестендіру.*

Авторлар туралы мәлімет

Турсунов Турсынхан Самгатович	Магистрант, Компьютерлік инженерия кафедрасы, Astana IT университеті, Астана, Қазақстан,E-mail: tursynkhan001@gamil.com ЖСН:020519551538 ,Мобильді номер: +77785331848 Пошта мекенжайы: 014690,ул. Куйши Дина 4А, кв 12
Кайбасова Динара	PhD, Компьютерлік инженерия кафедрасы, Astana IT университетінің қауымдастырылған профессоры, Астана, Қазақстан E-mail: Dinara.Kaibasova@astanait.edu.kz

Сведение об авторах

Турсунов Турсынхан Самгатович	Магистрант, кафедра компьютерной инженерии, Astana IT-университет, Астана, Казахстан, E-mail: tursynkhan001@gmail.com ИИН:020519551538, Мобильный номер: +77785331848 Почтовый адрес: 014690,ул. Куйши Дина 4А, кв 12
Кайбасова Динара	PhD, доцент, кафедра компьютерной инженерии, Astana IT-университет, Астана, Казахстан, E-mail: Dinara.Kaibasova@astanait.edu.kz

Information about the authors

Tursynkhan Tursunov Samgatovich	Master’s student, Department of Computer Engineering in Astana IT University, Astana, Kazakstan, E-mail: tursynkhan001@gmail.com IIN:020519551538, Mobile number: +77785331848 Postal address: 014690, st. Kuishi Dina 4A
Dinara Kaibassova	PhD, Associate Professor, Department of Computer Engineering in Astana IT University, Astana, Kazakstan, E-mail: Dinara.Kaibasova@astanait.edu.kz