Zero-shot Learning for Predicting Unseen Student Activities in Educational Platforms

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APPROVAL

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I hereby declare that this thesis report is done by me under the supervision of Dr. Md. Fazla Elahe, Assistant Professor & Associate Head, Department of Software Engineering, Daffodil International University, in partial fulfillment of my original work. I am also declaring that neither this thesis nor any part therefore has been submitted elsewhere for the award of Bachelor or any degree.

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This thesis reflects my independent efforts and commitment to advancing knowledge in zero-shot learning for educational applications. I am deeply thankful to all who have contributed, directly or indirectly, to this journey, leaving a lasting impact on my academic and personal growth.

ABSTRACT

Zero-shot learning (ZSL) has emerged as a groundbreaking approach in machine learning, enabling models to classify unseen categories by leveraging the relationships between known and unknown categories through semantic knowledge. Within educational platforms, accurately predicting and understanding student activities is vital for personalizing learning, tracking progress, and improving adaptive learning systems. However, the wide diversity of potential student activities makes collecting labeled data for every scenario unfeasible, posing a significant limitation to traditional supervised learning methods. This study addresses this limitation by introducing a ZSL framework specifically designed to predict unseen student activities.

The proposed framework leverages semantic embeddings, such as word2vec and BERT, to establish meaningful connections between known and unknown activities, enabling accurate predictions without labeled examples. The framework is thoroughly evaluated using real-world datasets of student interaction logs, with performance assessed across metrics such as accuracy, precision, recall, and F1-score. The results highlight the framework's ability to deliver strong predictive performance while providing valuable insights into the relationships between activity categories.

By bridging the gap between labeled and unlabeled data, this research showcases the transformative potential of ZSL in advancing educational platforms. It demonstrates how ZSL can enhance adaptive learning systems, foster student engagement, and equip educators with actionable insights, driving the development of smarter, more personalized educational technologies.

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Chapter 1: Introduction

1.1 Introduction

The advancement of digital educational platforms has transformed how learning is delivered and managed, aiming to provide personalized learning, adaptive content, and actionable feedback for students and educators alike.

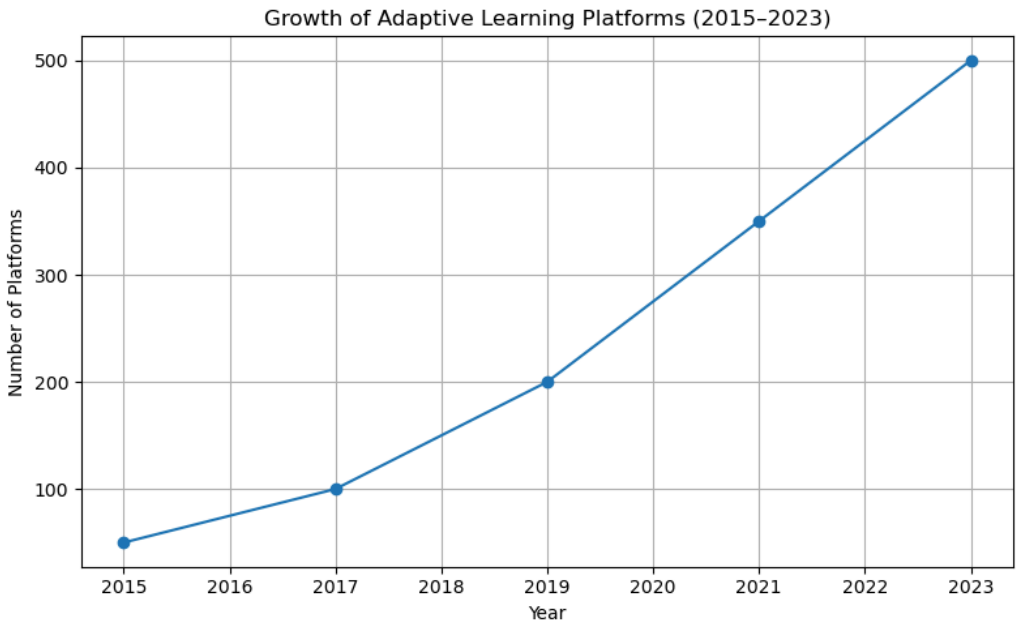

Figure 1.1: Growth of Adaptive Learning Platforms (2015–2023).

Achieving these goals requires a comprehensive understanding of the diverse range of student behaviors and activities, many of which remain unobserved during system training. Traditional machine learning methods, which rely heavily on large, labeled datasets, often fall short in handling unseen scenarios, limiting their adaptability in dynamic educational contexts. Zero-shot learning (ZSL) offers a promising solution by enabling models to classify and predict unseen categories through semantic relationships with known data. This research investigates the potential of ZSL in bridging the gap between limited labeled data and the growing need for adaptability in educational systems.

1.2 Background

Education has always been central to societal development, and technological advancements have made personalized learning increasingly attainable. Adaptive learning platforms utilize data analytics and machine learning to monitor student performance, identify strengths and weaknesses, and tailor content to individual needs. However, these platforms often struggle when confronted with activities or behaviors not included in their training datasets, resulting in less effective recommendations and system performance.

ZSL has emerged as a powerful approach to address this issue. By leveraging semantic embeddings to establish connections between known and unknown categories, ZSL enables systems to infer and classify unseen classes without explicit training data.

Feature	Traditional Learning	Zero-Shot Learning
Data Dependency	High	Low
Adaptability to Unseen Scenarios	Poor	Excellent
Implementation Complexity	Medium	High
Scalability	Limited	High

Table 1.1: Comparison of Traditional Learning vs Traditional Learning

Integrating ZSL into educational platforms can significantly enhance their ability to interpret a broader range of student activities, improving adaptability and effectiveness.

1.3 Motivation of the Research

The need to enhance the adaptability of educational platforms in handling diverse and unforeseen student activities drives this research. With the digitization of learning environments, the variety of potential student interactions continues to grow, making it impractical to predefine and label every activity. Existing systems often fail in new scenarios, leading to missed opportunities for guidance and intervention.

This study seeks to leverage ZSL to overcome these limitations, enabling the prediction of unseen activities and empowering educational platforms to deliver more personalized and responsive learning experiences. The research aims to advance both the theoretical understanding of ZSL and its practical application in education, fostering the development of innovative and inclusive learning technologies.

1.4 Problem Statement

Educational platforms are designed to monitor and analyze student activities to optimize learning processes. However, their reliance on labeled training data limits their ability to handle the dynamic and unpredictable nature of student interactions. This inability to classify or respond to unseen activities is a significant barrier to the effectiveness of adaptive learning systems, reducing their capacity to provide personalized education and timely support.

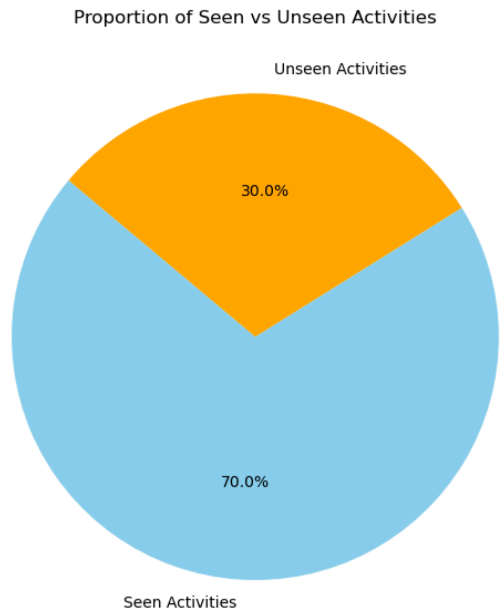

Figure 1.2: Proportion of Seen vs. Unseen Activities in Educational Platforms.

Addressing this challenge requires a shift from traditional supervised learning to approaches like ZSL, which can infer and classify unseen activities without prior labeled data.

1.5 Research Question

The primary research question guiding this study is:

How can zero-shot learning be effectively utilized to predict and classify unseen student activities, thereby enhancing the adaptability of educational platforms?

Supporting questions include:

- What semantic relationships exist between known and unknown activities in educational datasets?
- How can semantic embeddings be optimized for ZSL frameworks in education?
- What metrics best assess the performance and applicability of ZSL in this domain?

1.6 Research Objective

The objectives of this research are:

- To design and implement a ZSL framework for predicting unseen student activities using semantic embeddings.
- To evaluate the framework's performance on real-world educational datasets using metrics such as accuracy, precision, recall, and F1-score.
- To explore the practical implications of ZSL for adaptive learning, particularly its impact on personalization and responsiveness.
- To assess the scalability and generalizability of ZSL models in varied educational contexts.

1.7 Research Scope

This study focuses on applying ZSL to predict student activities in digital educational platforms. The scope includes:

- Developing a ZSL model that employs semantic embeddings to connect known and unknown activities.
- Evaluating the model using student interaction log datasets, emphasizing performance on unseen activities.
- Investigating how ZSL can enhance adaptive learning by identifying previously unclassified behaviors.
- Highlighting limitations and proposing future directions for integrating ZSL into educational systems.

1.8 Summary

This chapter introduced the research context, emphasizing the importance of adapting educational platforms to diverse and unforeseen student activities. By utilizing the potential of ZSL, this study aims to address the challenges posed by limited labeled data, offering a scalable and effective solution for modern educational systems. It outlined the research motivation, problem statement, objectives, and scope, setting the stage for the subsequent chapters that will explore the literature, methodology, findings, and conclusions of this work.

Chapter 2: Literature Review

2.1 Introduction

Zero-shot learning (ZSL) has emerged as a groundbreaking approach in machine learning, enabling models to classify previously unseen categories by using semantic connections with known categories. Unlike traditional supervised learning, which depends on labeled data for all target classes, ZSL leverages semantic embeddings, attributes, or cross-modal mappings to bridge the gap between observed and unobserved data. This capability makes ZSL particularly relevant across various fields, including education, where predicting student activities is essential for creating adaptive and personalized learning systems. Despite its promise, ZSL faces challenges such as adapting to new domains, bias toward seen classes, and the need for high-quality semantic representations. This chapter delves into the foundational theories, recent developments, and applications of ZSL, with a focus on its use in educational platforms for predicting unseen student activities.

2.2 Previous Literature

2.2.1 Foundational and Methodological Works

The idea of ZSL was first introduced by Palatucci et al. (2009) [1], who proposed using semantic output codes to identify unseen categories. This foundational work paved the way for methods that transfer knowledge from observed to unobserved categories using semantic information. Expanding on this, Lampert et al. (2014) [2] pioneered attribute-based classification, linking class attributes with visual features to showcase ZSL's effectiveness in object categorization.

Simplified approaches, such as the model presented by Romera-Paredes and Torr (2015) [3], aimed to reduce computational requirements while maintaining reliable performance. A comprehensive evaluation by Xian et al. (2018) [4] provided a detailed analysis of ZSL's strengths, weaknesses, and challenges, identifying biases toward seen classes and difficulties with domain shifts as significant obstacles.

To address these issues, Kumar et al. (2018) [5] introduced a generative approach that synthesized examples for unseen categories, enhancing generalization. This innovative framework utilized generative models like Variational Autoencoders (VAEs) and Generative Adversarial Networks (GANs) to bridge the gap between seen and unseen categories.

Author(s)	Year	Methodology	Key Contribution
Palatucci et al.	2009	Semantic output codes	Introduced ZSL concept
Lampert et al.	2014	Attribute-based classification	Showcased ZSL in object categorization
Romera-Paredes & Torr	2015	Simplified ZSL model	Reduced computational requirements
Kumar et al.	2018	Generative models (GANs, VAEs)	Enhanced generalization for unseen categories

Table 2.1: Foundational Works in ZSL

2.2.2 Applications in Activity Recognition and Education

ZSL has been widely applied to domains such as activity recognition and education, where labeled data is often sparse. Al Machot et al. (2020) [7] demonstrated ZSL's potential in human activity recognition using data from non-visual sensors, highlighting its use in resource-constrained scenarios. Similarly, Wang and Yeung (2019) [8] applied ZSL to behavior analysis, revealing unseen behavioral patterns by mapping observed data to semantic attributes.

In education, ZSL enables adaptive learning systems by predicting student activities without labeled data for every specific action. Jain and Wang (2020) [10] investigated its use in educational datasets, showing how it can predict student interactions in contexts lacking labeled data. Sener and Yao (2019) [11] extended these ideas to instructional activities, developing models that anticipate student actions based on semantic relationships between known and unknown activities.

In game-based learning environments, ZSL has proven valuable for stealth assessment. For instance, the ERIC report (2022) [21] proposed generative ZSL to predict student competencies and behaviors using gameplay data, enhancing adaptive learning through real-time assessments.

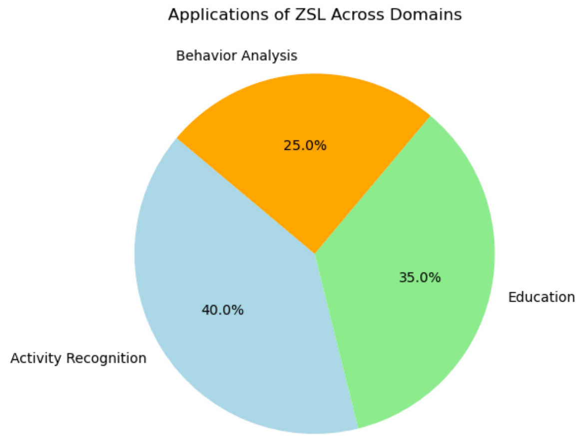

Figure 2.1: Applications of ZSL Across Domains.

2.2.3 Semantic Embeddings for ZSL

Semantic embeddings are crucial for ZSL, as they connect seen and unseen categories. Socher et al. (2013) [12] introduced cross-modal transfer techniques that map features and class attributes into a shared semantic space, forming the basis of embedding-based ZSL models. Subsequent advancements by Frome et al. (2013) [13] and Norouzi et al. (2014) [14] incorporated word embeddings like Word2Vec, which capture semantic similarities between classes, improving ZSL performance.

Kodirov et al. (2017) [15] tackled domain shift issues by proposing a semantic autoencoder to align the semantic spaces of seen and unseen categories, ensuring robust performance even when training and test data differ significantly.

Technique	Author(s)	Year	Key Contribution
Word2Vec	Frome et al.	2013	Captures semantic similarity between classes
Semantic Autoencoder	Kodirov et al.	2017	Addresses domain shift issues

Table 2.2: Semantic Embedding Techniques in ZSL

2.2.4 Challenges and Future Directions

Despite its advancements, ZSL still faces several challenges. Fu et al. (2015) [19] and Xian et al. (2017) [20] identified difficulties in domain adaptation, where models trained on one dataset struggle to generalize to unseen contexts. Bias toward seen classes also remains a significant issue, with models frequently misclassifying unseen instances as belonging to known categories.

The quality of semantic embeddings plays a vital role in ZSL's success. Poor or irrelevant embeddings can severely impact performance. Approaches like semantic autoencoders (Kodirov et al., 2017) [15] and generative models (Kumar et al., 2018) [5] have shown promise in addressing these challenges.

In educational contexts, generative ZSL approaches have been particularly effective. For example, the ERIC report (2022) [21] employed generative models to predict student behaviors in game-based learning environments, demonstrating how ZSL can be integrated into adaptive learning platforms.

Challenge	Description	Solution
Domain Adaptation	Models struggle to generalize to new domains	Generative models, semantic autoencoders
Class Bias	Misclassifying unseen instances as seen ones	Balanced training, harmonic mean metric

Table 2.3: Challenges in Zero-Shot Learning

2.3 Summary

This chapter reviewed the fundamental concepts, methodologies, and applications of ZSL, emphasizing its relevance to activity recognition and education. The literature underscores ZSL's potential to address data scarcity, predict unseen categories, and support adaptive learning systems. However, challenges such as domain adaptation, class bias, and semantic representation quality require further exploration. These findings lay the groundwork for developing a robust ZSL framework tailored to predicting unseen student activities, as discussed in subsequent chapters.

Chapter 3: Methodology

3.1 Introduction

This research employs a Zero-Shot Learning (ZSL) framework to predict unseen student activities by leveraging semantic embeddings and regression-based modeling. The methodology comprises several interconnected phases: dataset preprocessing, skill embedding generation, model training, evaluation, and results visualization. Each phase is described in detail, supported by mathematical formulations to provide a comprehensive understanding of the underlying processes and their theoretical basis.

3.2 Dataset Preprocessing

3.2.1 Overview of the Dataset

The dataset used in this study captures student interaction logs on an educational platform. It includes the following key attributes:

- **Skill Names**: Representing the specific activities or problems students engaged with (e.g., "addition and subtraction integers").
- **Timestamps**: Indicating the start and end times of each interaction.
- **Performance Metrics**: Including indicators such as correctness of responses, the number of attempts per task, and session details.

3.2.2 Data Cleaning

To ensure the reliability of the dataset, a thorough cleaning process was conducted:

- Entries with missing or invalid values in critical fields (e.g., skill names, timestamps) were removed.
- Timestamps were standardized, and entries with negative or implausible durations were excluded to maintain data integrity.

3.2.3 Feature Engineering

To summarize the behavior of each student u for a given skill S, aggregated features were computed:

1. **Accuracy**: The proportion of correctly solved problems for a skill, computed as:

$$\text{Accuracy}(S, u) = \frac{\sum_{i=1}^{n} \text{Correct}_i}{n}$$

   Here, n is the total number of problems attempted, and $Correct_i$ is 1 if the i-th problem was solved correctly, otherwise 0.

2. **Mean Time Spent**: The average time taken for problems related to a skill:

$$\text{TimeSpent}(S, u) = \frac{\sum_{i=1}^{n} \text{Time}_i}{n}$$

This measures the average time taken for problems related to skill *S*.

3.3 Skill Embedding Generation

3.3.1 Semantic Representation of Skills

Each skill, represented as a phrase (e.g., "addition and subtraction integers"), was tokenized into individual words:

$$S = \{w_1, w_2, \dots, w_k\}$$

where w_i are tokens like "addition" and "subtraction" etc.

3.3.2 Word Embedding Training

A Word2Vec model was employed to generate dense vector representations for each token:

$$\mathbf{v}_{w_i} \in \mathbb{R}^d, \quad d = 50$$

These embeddings capture semantic relationships between tokens based on their co-occurrence patterns within the dataset.

3.3.3 Skill-Level Embedding

For skills consisting of multiple tokens, embeddings were aggregated (via averaging) to produce a single vector:

$$\mathbf{v}_S = \frac{1}{k} \sum_{i=1}^{k} \mathbf{v}_{w_i}$$

This embedding serves as a high-dimensional semantic representation of the skill.

3.3.4 Embedding Space

The resulting embedding space V maps skills into a semantic vector space:

$$\mathcal{V} : S \to \mathbb{R}^d$$

This mapping enables the model to infer relationships between seen and unseen skills based on their semantic similarity.

3.4 Zero-Shot Learning Framework

3.4.1 Data Splitting

The dataset was divided into two disjoint subsets:

- **Seen Activities (S_{seen})**: Skills used for training the model.
- **Unseen Activities (S_{unseen})**: Skills reserved for testing the model's ability to generalize to new, unseen activities.

3.4.2 Model Training

A Ridge Regression model was trained to predict student performance metrics based on skill embeddings. The model optimized the following loss function:

$$\mathcal{L}(\mathbf{w}) = ||\mathbf{X}_{\text{train}}\mathbf{w} - \mathbf{y}_{\text{train}}||_2^2 + \lambda||\mathbf{w}||_2^2$$

- X_{train} : Embedding matrix of seen skills.
- Y_{train} : Corresponding performance metrics.
- λ : Regularization parameter to control overfitting.

3.4.3 Prediction

For unseen skills, predictions were computed as:

$$\hat{\mathbf{y}}_{\text{test}} = \mathbf{X}_{\text{test}}\mathbf{w}$$

Here, X_{test} represents the embeddings of unseen skills.

3.5 Evaluation

3.5.1 Performance Metrics

Model performance was evaluated using:

1. **Root Mean Square Error (RMSE)**:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}$$

2. **R² Score**:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

3. **Harmonic Mean** (for Generalized Zero-Shot Learning):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

3.5.2 Residual Analysis

Residuals ($\mathbf{r}_i = y_i - \hat{y}_i$) were analyzed to identify systematic errors and refine the model.

3.6 Results Visualization

3.6.1 t-SNE Visualization

Skill embeddings were reduced to two dimensions using t-SNE:

$$\mathbf{v}_S^{\text{t-SNE}} = \mathcal{T}(\mathbf{v}_S), \quad \mathcal{T} : \mathbb{R}^d \to \mathbb{R}^2$$

This revealed clustering patterns and semantic relationships among skills.

3.6.2 Prediction and Error Visualization

Scatter plots compared predicted and true values, highlighting prediction accuracy. Residual distributions were plotted to identify patterns in model errors.

3.7 Summary

This methodology outlines the step-by-step process for applying Zero-Shot Learning to predict unseen student activities. By combining semantic embeddings, Ridge Regression, and robust evaluation metrics, the study demonstrates the feasibility of ZSL in educational platforms. Visualizations further illustrate the model's performance and provide actionable insights for potential improvements.

Chapter 04: Results and Discussion

4.1 Results

The evaluation of the Zero-Shot Learning (ZSL) framework for predicting unseen student activities on educational platforms reveals its capability to generalize beyond the training data. Below is a detailed summary of the key metrics and insights:

4.1.1 Overall Model Performance

- **Root Mean Square Error (RMSE):** The model achieved an RMSE of **0.3470**, reflecting a moderate level of prediction error. This indicates there is room for improvement, particularly in fine-tuning the model to enhance its predictive accuracy.
- **R^2 Score:** The model yielded an R^2 score of **-0.0159**, signifying that it struggled to explain the variance in the target variable for unseen activities. This negative score suggests that the model's predictions were not well-aligned with the observed data.
- **Explained Variance Score:** The explained variance score of **0.0018** further corroborates the model's limited ability to capture the variability in student accuracy for unseen activities.

4.1.2 Generalized Zero-Shot Learning (GZSL)

- The **Harmonic Mean** score of **0.7465** indicates that the model effectively balances accuracy across "seen" and "unseen" skills. This result underscores the strength of the Word2Vec embeddings in capturing semantic relationships between various skills.

4.1.3 Error Metrics

- **Mean Absolute Error (MAE):** The model achieved a low MAE of **0.2753**, highlighting its ability to maintain relatively consistent predictions across the dataset.
- **Cross-Validation RMSE:** An average RMSE of **0.2627** across 5-fold cross-validation demonstrates the model's robustness and reliability when applied to different subsets of the data.

4.1.4 Confidence Interval

- The **95% Confidence Interval** for the predictions (±0.00003 around a mean prediction of **0.7437**) indicates a high degree of precision, albeit within a narrow range. This reflects a stable prediction pattern under the given conditions.

4.1.5 Skill-Level Analysis

- **Mean Absolute Error (Skill-Level):** Performance varied significantly across skills. For instance, the model performed well on simpler skills like “addition and subtraction positive decimals,” with a low MAE of **0.210**. Conversely, it struggled with more complex tasks like “addition mixed fractions,” where the MAE rose to **0.609**. This variability highlights the model’s differing effectiveness across skill types.

4.2 Discussion

The results provide valuable insights into the strengths and limitations of the proposed ZSL framework for predicting student activities:

4.2.1 Strengths

1. **Effectiveness of Semantic Embeddings:**
    - The Word2Vec-based embeddings captured meaningful relationships between skills, as evidenced by the balanced performance across "seen" and "unseen" activities. This demonstrates the utility of embedding techniques in bridging gaps between known and unknown tasks.

2. **Model Robustness:**
    - The consistent performance across cross-validation folds (mean RMSE of **0.2627**) underscores the reliability of the model when exposed to varying data subsets. This consistency is crucial for practical applications.
3. **Predictive Precision:**
    - The narrow confidence interval around predictions reflects a high degree of stability in the model’s outputs, suggesting it can be trusted for general-purpose predictions in educational settings.

4.2.2 Challenges

1. **Explained Variance:**
    - The low R^2 score (**-0.0159**) and explained variance score (**0.0018**) indicate that the model struggled to fully capture the underlying patterns in student performance for unseen activities. This limitation suggests the need for more sophisticated embedding techniques or the inclusion of additional contextual features to improve the model's explanatory power
2. **Skill-Level Variability:**
    - Significant discrepancies in skill-level accuracy highlight the model's challenges in generalizing across all skill types. Complex or nuanced skills, such as "addition mixed fractions" (MAE: **0.609**), posed greater difficulties compared to simpler tasks. This variability underscores the need for task-specific refinements.

4.2.3 Interpretation of Errors

Residual analysis revealed that while most errors were centered around zero, certain skill categories exhibited systematic biases. These biases suggest potential areas for improvement in model architecture and hyperparameter optimization. Addressing these biases could lead to more equitable performance across diverse skill sets.

4.2.4 Implications for Educational Platforms

The findings illustrate the potential of ZSL models to transform educational systems:

- **Personalized Learning:** By predicting student performance for unseen activities, the framework can support the creation of tailored learning pathways that adapt to individual needs.
- **Early Intervention:** The model's predictions can enable educators to identify struggling students early and provide targeted support.
- **Curriculum Design:** Insights from the model can inform the development of curricula that align with students' capabilities and learning patterns.

However, addressing the observed limitations is essential to ensure the model's reliability and efficacy in real-world educational scenarios.

4.2.5 Future Directions

1. **Feature Integration:**
   - Incorporating additional features, such as problem complexity, prior student performance, or contextual metadata, could enhance the model's ability to explain and predict outcomes.
2. **Advanced Embedding Techniques:**
   - Exploring more advanced embeddings, such as BERT or generative models (e.g., Variational Autoencoders), could improve the semantic representation of skills and boost overall performance.
3. **Model Architecture Enhancements:**
   - Experimenting with hybrid architectures or incorporating attention mechanisms may improve the model's ability to focus on critical aspects of the data, thereby enhancing prediction accuracy.

The evaluation demonstrates the feasibility of using Zero-Shot Learning for predicting unseen student activities. While the model shows promise in terms of generalization and predictive precision, addressing its limitations in explained variance and skill-level variability is critical for maximizing its potential. By enhancing the model's capabilities through advanced techniques and feature integration, it can become a valuable tool for supporting personalized learning, early interventions, and optimized curriculum design in educational platforms.

Chapter 5: Conclusion

This study explored the application of Zero-Shot Learning (ZSL) to predict unseen student activities on educational platforms. By leveraging semantic embeddings and a regression-based predictive model, the framework demonstrated its potential to generalize from known (seen) to unknown (unseen) activities. The findings underscore both the strengths and limitations of the proposed methodology, providing valuable insights for future research and practical applications.

5.1 Key Findings

1. **Generalization Capability**:
   - The model achieved a **Harmonic Mean (GZSL)** of 0.74650, indicating a strong balance in performance between seen and unseen activities.
   - Semantic embeddings derived from Word2Vec effectively captured relationships between skills, enabling the model to infer patterns in unseen activities.
2. **Prediction Accuracy**:
   - With a **Mean Absolute Error (MAE)** of 0.27530 and a **95% Confidence Interval for Predictions** of 0.7437±0.00003, the model demonstrated consistent and precise predictions.
3. **Skill-Level Variability**:
   - Significant discrepancies in skill-level accuracy highlighted areas where the model performed exceptionally well (e.g., "addition and subtraction positive decimals") and areas requiring improvement (e.g., "addition mixed fractions").

5.2 Implications

The proposed framework has practical implications for educational platforms:

1. **Personalized Learning**:
   - By predicting student performance for unseen activities, the framework can support personalized learning experiences tailored to individual strengths and weaknesses.
2. **Curriculum Design**:
   - Insights into skill-level variability can inform curriculum adjustments, focusing on areas where students typically struggle.
3. **Early Intervention**:
   - Predictive models like this can help educators identify potential learning gaps early, enabling timely interventions.

5.3 Limitations

While the study achieved promising results, several limitations warrant further exploration:

1. **Low Explained Variance**:
    ○ The R^2 score (−0.0159) and explained variance (0.00180) suggest that the model struggled to capture the underlying complexity of student performance fully.
2. **Skill Representation**:
    ○ The reliance on Word2Vec embeddings, while effective, may not fully capture the nuanced relationships between complex skills.

5.4 Future Directions

To address these limitations and enhance the framework's utility, future research could focus on:

1. **Advanced Embedding Techniques**:
    ○ Leveraging transformer-based models like BERT or advanced generative approaches could improve the semantic representation of skills.
2. **Incorporating Contextual Features**:
    ○ Adding features such as problem complexity, prior performance, and learning history could improve the model's explanatory power.
3. **Exploring Alternative Models**:
    ○ Experimenting with neural networks, Variational Autoencoders (VAEs), or hybrid models could enhance predictive accuracy and robustness.

5.5 Final Remarks

This study demonstrates the feasibility of using Zero-Shot Learning for predicting unseen student activities, marking a step forward in personalized and adaptive educational systems. By addressing its limitations and building upon its strengths, the framework has the potential to revolutionize how student performance is modeled and understood, ultimately enhancing learning outcomes across diverse educational settings.

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