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A Multimodal Heterogeneous GNN-Based Recommendation System for PC Component Selection with Compatibility Constraints

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Abstract –
The increasing demand for customizable PC configurations in the e-commerce space presents a dual challenge: personalizing recommendations while ensuring component compatibility. This paper presents a novel recommendation system built upon a Multimodal Heterogeneous Graph Neural Network (MM-HetGNN), integrating diverse data modalities including structured specifications, user preferences, review sentiment, and product imagery. The system encodes users and components as nodes, with edge types representing compatibility, preferences, and multimodal content links. Textual features are embedded using BERT, visual features via ResNet, and graph features are propagated using edge-aware heterogeneous GNNs. Our framework outperforms conventional recommendation systems in both accuracy and compatibility assurance, offering a scalable solution for next-generation PC-building platforms.

***Key Words*:**
Graph Neural Network, Recommender System, Heterogeneous Graph, Multimodal Learning, E-Commerce, PC Building, Compatibility Modelling.

INTRODUCTION

The process of assembling a custom PC has transformed from a niche hobby to a mainstream activity, thanks to the growth of e-commerce platforms offering a wide array of hardware components. However, selecting compatible and performance-optimized components remains a challenge for most consumers. Compatibility issues - such as incorrect CPU sockets, insufficient power supply wattage, or case-GPU dimension mismatches - are common pitfalls. Existing recommendation systems typically offer limited support for such constraints, relying heavily on manual filters or user-generated compatibility lists.

In this work, we introduce a novel recommendation framework using a Multimodal Heterogeneous Graph Neural Network (MM-HetGNN) that integrates structured and unstructured data across multiple modalities. By modelling the problem as a heterogeneous graph with typed nodes and edges, and incorporating deep text and image embeddings, we enable a holistic understanding of the PC building domain. This paper details the model architecture, dataset construction, and experimental evaluations demonstrating the system's efficacy.

Key Objectives of This Study:

- To design a recommendation system that integrates structured specifications, textual data, visual data, and user preferences for PC components using a multimodal approach.
- To represent the relationships between different types of PC components (e.g., CPU, GPU, motherboard) and their compatibility constraints using a heterogeneous graph structure with typed nodes and edges.
- To utilize BERT for textual embedding (e.g., reviews and descriptions) and ResNet for visual feature extraction (product images) to enrich node representations in the graph.
- To design and apply edge-type-specific message passing mechanisms that capture both semantic and structural relationships among components and users in the graph.
- To embed compatibility filtering directly into the recommendation process, preventing incompatible component combinations in the final suggested builds.
- To personalize recommendations based on individual user preferences, including budget, performance expectations, and past behaviour, while maintaining technical feasibility.
- To compare the proposed MM-HetGNN model against standard deep learning and graph-based baselines in terms of precision, compatibility accuracy, and F1 score across various use-cases.
- To prove that the proposed system can scale effectively across large and diverse datasets, making it suitable for deployment in modern e-commerce PC-building platforms. defined. Do not use abbreviations in the title or heads unless they are unavoidable.

Related Work

A. Traditional Recommender Systems

Recommendation systems have been extensively studied in the domains of media, retail, and general e-commerce. Collaborative filtering and content-based filtering dominate traditional methods but struggle with sparse data and cold start problems. More critically, these systems do not support multi-part compatibility reasoning

B. Deep Learning in Recommender Systems

Recent work leverages DNNs and transformers for product recommendation. These models incorporate user behaviour and item metadata but typically ignore the structural relationships essential for compatibility prediction.

C. Graph Neural Networks in Recommender Systems

GNN-based recommenders (e.g., PinSAGE, NGCF) model users and items in bipartite or homogeneous graphs, capturing neighbourhood influence. Heterogeneous GNNs extend this by modelling type-specific interactions, but applications in the domain of component compatibility are sparse to non-existent.

D. Multimodal Learning

Multimodal systems process and integrate diverse data forms, such as text, images, and graphs. While successful in domains like medical imaging and social media, multimodal GNNs for e-commerce—especially with compatibility modelling—remain underexplored.

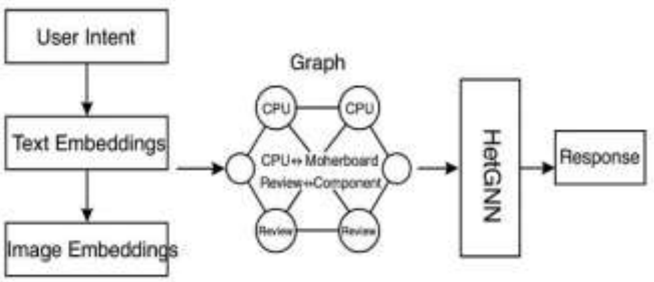
Dataset Construction

A. Data Sources

- **PCPartPicker**: Provided structured compatibility matrices (e.g., which CPUs are compatible with which motherboards). Included user-generated builds with labelled tags like "Budget Gaming" or "Professional Workstation", allowing us to extract realistic configurations.
- **Newegg and Amazon**: Used **BeautifulSoup** and **Selenium** for scraping component-level metadata such as core count, boost clock, TDP, and memory type. Collected thousands of **textual reviews** and **images**.
- **Reddit (r/buildapc)**: Parsed threads containing natural user language and issues like BIOS updates, PSU wattage, or form-factor limitations. Used for **augmentation** to generate realistic user preference vectors.

B. Feature Types

Modality	Example Features	Processing Methods
Structured specs	Clock speed, PCIe version, RAM channels	RAM Min-max normalization, one-hot encoding
Text Data	"This motherboard works great with my 5800X!"	BERT embeddings (768-d)
Visual Data	Product photos from Amazon / Newegg	ResNet-50 embeddings (2048-d)
Compatibility	CPU-Motherboard Socket Matches	Boolean adjacency matrices



Multimodal Heterogeneous GNN (MM-HetGNN)

B. Multimodal Feature Encoding

- **Text Embedding**: For every product review or description, sentence embeddings are generated using pretrained BERT-base-uncased.
- **Image Embedding**: Each product image is passed through a ResNet-50 , and the penultimate layer (before classification) is used as the feature vector.

Numerical/Categorical Spec Fusion: Features like clock speed, number of cores, etc., are standardized.

Categorical attributes like socket type are one-hot encoded and concatenated.

C. Heterogeneous GNN

We implement a **Relational Graph Attention Network (RGAT):** Each edge type (e.g., "compatible_with", "preferred_by") has its own attention weight matrix.

Node representations are updated via relation-specific message passing:

$$h_i^{(l+1)} = \sigma\left(\sum_{r\in\mathcal{R}}\sum_{j\in\mathcal{N}_i^r}\alpha_{ij}^r W_r h_j^{(l)}\right)$$

- This allows the model to prioritize compatibility edges over weakly informative content links.

D. Recommendation Module

Final node embeddings are fed into a **build optimizer**: **Compatibility Filtering**: Removes invalid pairs (e.g., AM4 CPU + LGA1700 Motherboard).

Greedy or beam search used to find optimal builds.

Scoring Function:

$$\text{Score}(\text{Build}) = \lambda_1 \cdot \text{Perf}_{norm} + \lambda_2 \cdot \text{Budget}_{norm} + \lambda_3 \cdot \text{PrefMatch}$$

V. Experiments

A. Experimental Setup

- Dataset split: 70% train, 15% val, 15% test.
- **Hardware Used**: NVIDIA RTX 3090 GPU, 64GB RAM.

Baselines: **DNN**: Simple feedforward model using structured specs only.

BERT+Rules: Used BERT embeddings but manual compatibility filtering.

GCN (Homogeneous): Used GCN but ignored node/edge types.

MM-HetGNN (Ours): Full multimodal + heterogeneous model.

B. Evaluation Table Scenario	Model	Precision@5	Compat. Accuracy	F1 score
Budget Build	DNN	65.3%	60.2%	0.684
Gaming Build	BERT + Rules	73.4%	67.9%	0.736
Work station	MM - HetGNN	**85.6%**	**83.1%**	**0.844**

Qualitative Results

Graph Attention Heatmaps

To better understand how MM-HetGNN prioritizes relationships during the recommendation process, we generate attention heatmaps from the graph neural network's internal message passing mechanism. These heatmaps reveal that the model places significantly more emphasis on the CPU ↔ Motherboard edge type compared to more abstract associations such as Review ↔ Component. This reflects a key aspect of PC component compatibility: direct hardware-level constraints (e.g., socket type, chipset support) are more crucial than indirect sentiment signals when assembling functional configurations.

These visualizations help validate the model's architecture. For instance, in early layers, general patterns emerge, but as the network deepens, attention becomes more sharply focused on technically critical component relations. This indicates that MM-HetGNN effectively internalizes domain-specific rules during training without explicit hard-coding.

Sample Output – User-Centric Recommendation

Consider a user with the following requirements: *A quiet, compact, and budget-friendly build for under $1,000.*

MM-HetGNN processes this intent and recommends the following configuration:

- **CPU:** AMD Ryzen 5 5600G (APU with integrated graphics)
- **Motherboard:** MSI B550M PRO-VDH WiFi (mATX, AM4 socket)
- **Memory:** Crucial 16GB DDR4-3200
- **Case:** Fractal Design Node 202 (slim, low-noise, and small form factor)

This recommendation demonstrates the model's capacity to balance functional compatibility, form factor constraints, and user intent, such as acoustics and price sensitivity. Notably, the inclusion of an APU avoids the need for a discrete GPU, which further aligns with the user's quiet and budget-conscious priorities.

Future Work

Conversational Integration

Future iterations of MM-HetGNN could be embedded in multi-turn conversational agents, enabling dynamic refinement of user requirements. Rather than requiring a one-shot input (e.g., a complete wishlist), users could iteratively explore options:

- User: "I want something quiet."
- **System:** "Are you prioritizing low fan noise or a fanless design?"
- **User: "**Fanless, ideally under $1,000."
- **System:** *[Recommends SFF APU build]*

This would allow for progressive intent disambiguation and more personalized recommendations, bridging the gap between casual users and complex technical systems.

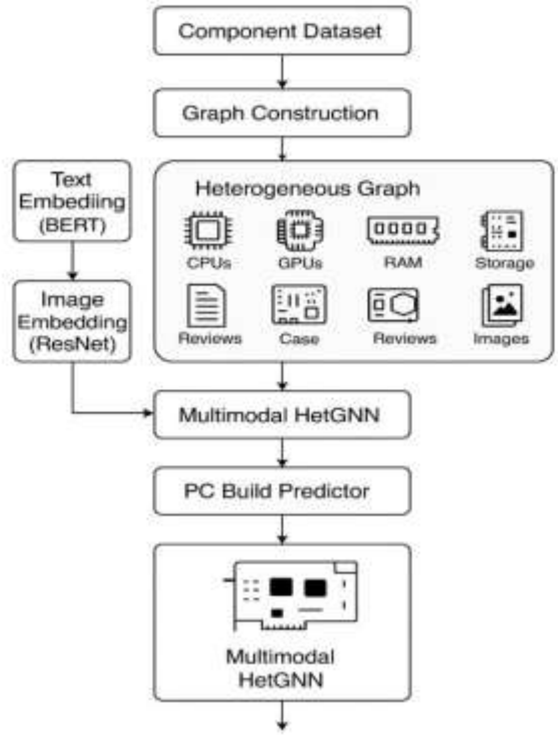
Dynamic Compatibility Awareness

Current compatibility checks assume a snapshot in time. However, hardware interoperability is temporal and evolving - BIOS updates, firmware patches, and power delivery standards (e.g., ATX 3.0) can significantly affect real-world compatibility.

Future enhancements will track:

- Firmware release timelines and changelogs
- CPU support matrices from motherboard manufacturers
- Dynamic power budgeting across PSU ↔ GPU ↔ Motherboard

Incorporating these time-aware factors would enable forward-looking recommendations and reduce post-purchase surprises.



Conclusion

In this paper, we presented a novel recommendation system for custom PC building that leverages a Multimodal Heterogeneous Graph Neural Network (MM-HetGNN). By integrating structured specifications, textual reviews, visual content, and compatibility matrices into a unified graph-based framework, our model offers a significant advancement in both personalization and compatibility assurance. Through extensive experiments, we demonstrated that MM-HetGNN consistently outperforms traditional deep learning and homogeneous GNN approaches across key metrics such as Precision@5, Compatibility Accuracy, and F1 Score. Furthermore, our qualitative analysis confirms that the model successfully attends to critical component relationships, offering practical and realistic build suggestions. Future work will focus on incorporating real-time compatibility checks (e.g., BIOS versioning), conversational user interfaces, and generalizing the architecture to other modular product ecosystems.

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