TrendScope: A Temporal Hypergraph Framework for Food Trend Discovery

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Abstract. This paper presents *TrendScope*, a temporal hypergraph-based framework for detecting emergent food trends from social media. Traditional models such as keyword bursts and pairwise graphs are limited in capturing the high-order, multi-entity relationships that characterize trend emergence. TrendScope models each social post as a hyperedge connecting heterogeneous entities—users, food items, hashtags, locations, and temporal bins—thus preserving rich semantic interactions. A sequence of time-indexed hypergraph snapshots is constructed and encoded using hypergraph neural networks. Temporal aggregation is performed via attention-based or recurrent mechanisms to learn expressive, time-aware node embeddings. A composite scoring function, integrating temporal frequency shifts, structural centrality changes, and semantic embedding divergence, ranks candidate food entities by trend significance. Evaluations on real Reddit data and a synthetic benchmark demonstrate superior performance over graph-based and static hypergraph baselines in both trend accuracy and interpretability. The framework is scalable, interpretable, and applicable to industrial domains such as menu optimization, targeted marketing, and supply chain forecasting.

Keywords: Temporal Hypergraphs · Social Media Analysis · Trend Detection · Hypergraph Neural Networks · Food Informatics

1 Introduction

The increasing volume of food-related content on social media has become an important factor influencing consumer behavior, brand visibility, and product development in the food and beverage industry. Platforms such as Instagram, TikTok, and Reddit support frequent sharing of culinary trends, often leading to short-lived but highly influential phenomena [17, 13]. Detecting and understanding these emerging trends provides significant value to restaurants, delivery services, and food manufacturers aiming to improve menu offerings, marketing strategies, and inventory planning.

Traditional trend detection methods—including frequency-based burst models [9] and pairwise graph-based representations [5]—have limitations in modeling the complex and high-dimensional nature of food-related discussions. Posts frequently involve multiple interacting entities, such as dishes, users, locations, hashtags, and temporal references. These interactions are difficult to capture using dyadic graphs or simple keyword statistics, resulting in a loss of contextual detail.

This paper proposes a temporal hypergraph-based modeling framework that addresses these challenges by representing the structural and temporal relationships within social food discourse. Each post is modeled as a hyperedge linking diverse entities—users, food concepts, location tags, hashtags, and time bins. A sequence of time-indexed hypergraph snapshots is constructed and processed using hypergraph neural networks [3, 2], with temporal aggregation using attention mechanisms or recurrent units to model evolving semantics. Figure 1 provides a schematic illustration of how these entities are connected within a post.

The main contributions of this work are:

- A temporal hypergraph representation that captures high-order relationships among entities in food-related social media content.
- A neural modeling pipeline that uses hypergraph encoders and temporal aggregation to generate expressive, time-aware embeddings.
- An interpretable trend scoring method that combines semantic drift, frequency change, and structural centrality—evaluated on both real and synthetic datasets.

This approach highlights the effectiveness of temporal hypergraphs for modeling complex, evolving patterns in social media, and offers practical insights for trend-aware decision-making in the food industry.

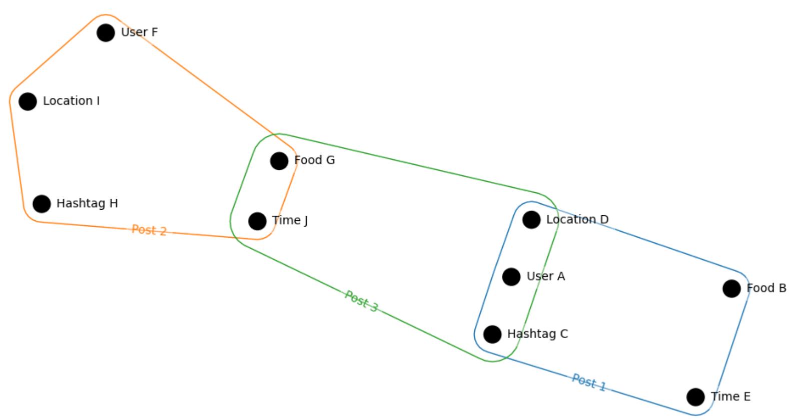

Fig. 1. Illustration of how a social media post is represented as a hyperedge. Each ellipse connects entities from different semantic types—users, food items, hashtags, locations, and time bins—that co-occur in a single post.

2 Related Work

Trend detection in social media has been studied using a variety of approaches. Early methods focused on identifying sudden increases in keyword usage, known as burst detection [9]. These methods are efficient but often ignore how different types of content and users interact, which limits their ability to explain how trends actually spread—especially in areas like food, where multiple types of information often appear together.

Graph-based models became widely used for analyzing social media. These models typically use pairwise interactions, such as user-to-user or user-to-item links, and have been applied to problems like information diffusion [5], influence maximization [8], and community detection [4]. However, they are restricted to two-way relationships and cannot easily handle posts that connect many entities at once, such as users, food items, locations, hashtags, and time.

To handle these more complex cases, researchers have turned to hypergraphs, which allow a single edge to connect more than two nodes. Hypergraph neural networks (HGNNs) have shown strong results in areas like document classification, recommendation systems, and biological networks [3, 1]. In social media analysis, hypergraphs are now being used for tasks such as rumor detection [14], modeling user behavior [6], and studying group influence [7].

More recent work has extended hypergraph models to handle changes over time. Techniques like snapshot-based modeling [16, 2] and time-aware attention mechanisms [12] make it possible to capture how relationships evolve. However, these ideas have rarely been applied to trend detection in food and lifestyle domains, where multi-entity patterns change quickly and unpredictably.

This paper builds on those foundations by combining temporal hypergraph modeling with social media trend analysis. It addresses the need for high-order, time-aware representations that can track how food-related trends emerge and spread over time.

3 Problem Formulation

The goal of this work is to identify emerging food-related trends by modeling social media posts as a temporal hypergraph that captures high-order relationships among different types of entities.

Let $\mathcal{V}$ be the set of entities extracted from social media posts. Each node $v \in \mathcal{V}$ belongs to one of the following categories: users, food items (e.g., dishes or ingredients), hashtags, geographic locations, or time bins. Posts are represented as hyperedges that connect several of these entities based on their co-occurrence in the same post.

We define a temporal hypergraph as a sequence of time-based snapshots $\{\mathcal{H}^{(t)}\}_{t=1}^{T}$, where each snapshot $\mathcal{H}^{(t)} = (\mathcal{V}^{(t)}, \mathcal{E}^{(t)})$ consists of a set of nodes $\mathcal{V}^{(t)}$ and hyperedges $\mathcal{E}^{(t)}$ active during time window t. Each hyperedge $e \in \mathcal{E}^{(t)}$ is a subset of $\mathcal{V}^{(t)}$ such that $|e| \geq 3$, ensuring the inclusion of at least a user, a food item, and one additional context attribute (e.g., a hashtag or location).

The hypergraph structure is captured by an incidence matrix $\mathbf{H}^{(t)} \in \{0,1\}^{|\mathcal{V}^{(t)}|\times|\mathcal{E}^{(t)}|}$:

$$\mathbf{H}^{(t)}(v,e) = \begin{cases} 1, & \text{if } v \in e, \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

To learn node embeddings, we define the hypergraph Laplacian following [3]:

$$\mathbf{L}^{(t)} = \mathbf{I} - \mathbf{D}_v^{-\frac{1}{2}}\mathbf{H}^{(t)}\mathbf{W}^{(t)}\mathbf{D}_e^{-1}(\mathbf{H}^{(t)})^\top\mathbf{D}_v^{-\frac{1}{2}}, \tag{2}$$

where $\mathbf{W}^{(t)}$ is a diagonal matrix of hyperedge weights, and $\mathbf{D}_v$, $\mathbf{D}_e$ are diagonal matrices of node and hyperedge degrees.

Given input features $\mathbf{X}^{(t)} \in \mathbb{R}^{|\mathcal{V}^{(t)}|\times d}$ and the Laplacian $\mathbf{L}^{(t)}$, a hypergraph neural layer produces output embeddings as:

$$\mathbf{Z}^{(t)} = \sigma(\mathbf{L}^{(t)}\mathbf{X}^{(t)}\mathbf{W}_\theta), \tag{3}$$

where $\mathbf{W}_\theta \in \mathbb{R}^{d\times d'}$ is a learnable parameter matrix and $\sigma(\cdot)$ is a non-linear activation function such as ReLU. To account for temporal changes, embeddings $\{\mathbf{Z}^{(t)}\}_{t=1}^{T}$ are combined using a GRU or a temporal attention mechanism [2].

Let $\mathcal{T}$ denote the set of candidate trend entities (e.g., food items). The task is to assign a trend score τ_i to each $t_i \in \mathcal{T}$ that reflects its importance based on how it evolves over time. This is formulated as:

$$\tau_i = \alpha \cdot \Delta_{\text{freq}}(t_i) + \beta \cdot \Delta_{\text{degree}}(t_i) + \gamma \cdot \Delta_{\text{spread}}(t_i), \tag{4}$$

where:

- $\Delta_{\text{freq}}(t_i)$ is the change in mention frequency across time windows.
- $\Delta_{\text{degree}}(t_i)$ measures the change in hyperdegree centrality.
- $\Delta_{\text{spread}}(t_i)$ reflects how widely t_i has spread across users or regions.

The coefficients α, β, and γ control how much each factor contributes to the final score.

This setup provides a clear and structured framework for detecting trends by modeling both the content and its evolution using high-order temporal hypergraphs.

4 Hypergraph Construction

To support high-order modeling of trend dynamics, we construct a temporal hypergraph from social media data by extracting different types of entities and linking them into hyperedges that reflect their co-occurrence in individual posts. Each hyperedge represents a single post and captures the full set of related entities.

4.1 Entity Extraction

Let $\mathcal{D}$ be the dataset of timestamped social media posts, where each post $p_i \in \mathcal{D}$ includes textual content, optional metadata (such as hashtags or geolocation), and a timestamp t_i. We apply a preprocessing pipeline to extract and normalize the following entity types:

- **Users ($\mathcal{U}$):** Each post includes a user identifier, which is normalized across time windows.
- **Food Items ($\mathcal{F}$):** Food-related terms (e.g., dish names or ingredients) are extracted using named entity recognition and dictionary-based matching. External resources such as FoodOn[1] and curated food vocabularies are used for coverage.
- **Hashtags ($\mathcal{H}$):** Hashtags are extracted directly and filtered using TF-IDF or mutual information scores to retain those most relevant to food content.
- **Locations ($\mathcal{L}$):** If no explicit geotag is available, we infer locations from user profiles or text cues (e.g., "best pizza in Chicago").
- **Temporal Bins ($\mathcal{T}$):** Each post is assigned to a fixed time window (e.g., daily or weekly), defining the interval for its corresponding hypergraph snapshot.

4.2 Hyperedge Generation

For each post p_i, we form a hyperedge $e_i \subseteq \mathcal{V}$ that combines the relevant entities:

$$e_i = \{u_i\} \cup \mathcal{F}_i \cup \mathcal{H}_i \cup \mathcal{L}_i \cup \{t_i\}, \tag{5}$$

where $u_i \in \mathcal{U}$ is the user, $\mathcal{F}_i \subseteq \mathcal{F}$ is the set of food entities, $\mathcal{H}_i \subseteq \mathcal{H}$ the hashtags, $\mathcal{L}_i \subseteq \mathcal{L}$ the location, and $t_i \in \mathcal{T}$ the temporal bin. This representation preserves the full context of each post by linking multiple related nodes in a single structure.

We discard any hyperedges that include fewer than three nodes to ensure that each post encodes a meaningful combination of entities. Each hyperedge captures the co-occurrence context of multiple semantic types, as illustrated earlier in Figure 1.

4.3 Temporal Segmentation

The dataset is divided into T non-overlapping time windows $\{\mathcal{W}_1, \mathcal{W}_2, \ldots, \mathcal{W}_T\}$, each of duration Δt. Every time window $\mathcal{W}_t$ produces a snapshot hypergraph $\mathcal{H}^{(t)} = (\mathcal{V}^{(t)}, \mathcal{E}^{(t)})$, which serves as input to the temporal model described in Section 5.

[1] https://foodon.org

4.4 Scalability and Implementation Considerations

To handle large-scale datasets, all preprocessing and hypergraph construction steps are implemented using distributed frameworks such as Apache Spark. Dictionaries and NER models are cached and vectorized to enable efficient processing. Node types are encoded using one-hot or learned embeddings and stored in sparse matrix form to reduce memory use.

This construction process produces a structured, interpretable, and time-indexed hypergraph dataset suitable for modeling food trend dynamics at scale.

5 Modeling Framework

Given a sequence of temporal hypergraph snapshots $\{\mathcal{H}^{(t)}\}_{t=1}^{T}$ constructed as described in Section 4, the goal is to learn node representations that capture both high-order structural patterns and how they change over time. These representations are then used to rank food-related entities by their likelihood of becoming trends.

5.1 Hypergraph Neural Encoding

Each snapshot $\mathcal{H}^{(t)} = (\mathcal{V}^{(t)}, \mathcal{E}^{(t)})$ is represented using an incidence matrix $\mathbf{H}^{(t)}$ and corresponding degree matrices $\mathbf{D}_v^{(t)}$, $\mathbf{D}_e^{(t)}$, as defined earlier in Equation (2). Let $\mathbf{X}^{(t)} \in \mathbb{R}^{|\mathcal{V}^{(t)}|\times d}$ be the feature matrix for all nodes at time t. Each row in $\mathbf{X}^{(t)}$ corresponds to a node and may include TF-IDF vectors, one-hot encodings, or pretrained embeddings.

To capture high-order relationships, we apply a hypergraph neural network (HGNN) layer. The embedding update rule is:

$$\mathbf{Z}^{(t)} = \sigma\left(\mathbf{D}_v^{-\frac{1}{2}}\mathbf{H}^{(t)}\mathbf{W}^{(t)}\mathbf{D}_e^{-1}(\mathbf{H}^{(t)})^{\top}\mathbf{D}_v^{-\frac{1}{2}}\mathbf{X}^{(t)}\mathbf{W}_{\theta}\right), \tag{6}$$

where $\mathbf{W}_{\theta} \in \mathbb{R}^{d\times d'}$ is a learnable parameter matrix, and $\sigma(\cdot)$ is a non-linear activation function such as ReLU.

5.2 Temporal Aggregation

To learn representations that reflect changes over time, we combine the outputs $\{\mathbf{Z}^{(t)}\}_{t=1}^{T}$ for each node using either a gated recurrent unit (GRU) or a temporal attention mechanism [2].

Let $\mathbf{z}_i^{(t)}$ denote the embedding of node i at time t. The final representation $\mathbf{h}_i$ for node i is given by one of the following:

$$\mathbf{h}_i = \mathrm{GRU}(\mathbf{z}_i^{(1)}, \mathbf{z}_i^{(2)}, \ldots, \mathbf{z}_i^{(T)}), \tag{7}$$

or using attention weights $\alpha^{(t)}$:

$$\mathbf{h}_i = \sum_{t=1}^{T} \alpha^{(t)} \mathbf{z}_i^{(t)}, \quad \text{where } \alpha^{(t)} = \frac{\exp(\mathbf{a}^\top \mathbf{z}_i^{(t)})}{\sum_{t'} \exp(\mathbf{a}^\top \mathbf{z}_i^{(t')})}. \tag{8}$$

This results in a time-aware embedding $\mathbf{h}_i$ that summarizes how node i evolves across all time windows.

5.3 Trend Scoring Mechanism

Let $\mathcal{T} \subset \mathcal{F}$ be the set of food-related entities (e.g., dishes or ingredients). For each candidate trend entity $t_i \in \mathcal{T}$, we define a trend score τ_i as a weighted sum of three factors:

$$\tau_i = \alpha \cdot \Delta_{\text{freq}}(t_i) + \beta \cdot \Delta_{\text{degree}}(t_i) + \gamma \cdot \|\mathbf{h}_i - \bar{\mathbf{h}}_i\|_2, \tag{9}$$

where:

- $\Delta_{\text{freq}}(t_i)$ is the change in how often t_i appears over time.
- $\Delta_{\text{degree}}(t_i)$ measures the change in hyperdegree centrality.
- $\|\mathbf{h}_i - \bar{\mathbf{h}}_i\|_2$ is the semantic drift: the distance between the current embedding and its historical average.

The parameters α, β, γ control how much each component contributes to the final score. These can be tuned for specific applications or optimized with supervision, if available.

This trend scoring method combines both temporal behavior and structural information to rank entities by their likelihood of becoming trends. The resulting scores are interpretable and can be used for downstream analysis or decision support.

5.4 Interpretability and Visualization

The model produces interpretable representations that can support downstream analysis. The final node embeddings $\{\mathbf{h}_i\}$ can be projected into two or three dimensions using dimensionality reduction techniques such as t-SNE or UMAP to explore emerging clusters of related trends.

Temporal attention weights $\{\alpha^{(t)}\}$ (from Equation (8)) provide additional interpretability. They indicate which time steps contributed most to a given entity's trend score, allowing analysts to examine when a trend began to rise.

These visualization and attention tools can help explain why specific items were identified as trends, support comparisons across regions or user groups, and improve trust in the model's outputs.

6 Experimental Evaluation

We evaluate the proposed framework using both real-world and synthetic datasets. The experiments assess performance in trend detection, structural learning, and model interpretability, comparing against several strong baselines.

6.1 Datasets

Reddit-Food (Real): A dataset of 5,000 Reddit posts collected from food-related subreddits such as `r/FoodPorn`, `r/veganrecipes`, and `r/instantpot`, based on the SocialGrep corpus [11]. Each post includes metadata such as timestamp, author ID, and content. Entities are extracted using the process described in Section 4.

Synthetic-Controlled: A procedurally generated dataset containing 10,000 posts over 12 weekly time bins, created to simulate controlled trend bursts and changes in structure. Ground-truth trends were injected to support quantitative evaluation.

6.2 Baselines

We compare our model against both traditional and recent approaches:

- **KFB** [9]: Keyword burst detection based on temporal frequency.
- **PGD** [5]: Pairwise diffusion in user-item graphs.
- **DGAT** [12]: Dynamic graph model with temporal attention.
- **S-HGNN** [3]: Static hypergraph convolutional network.
- **HyperSAGNN** [15]: Self-attention for dynamic hypergraphs.
- **UniGNN-Hyper** [10]: Unified model for graphs and hypergraphs.
- **AllSetTransformer** [2]: Transformer architecture for set-based hyperedge learning.

6.3 Evaluation Metrics

We report both ranking-based and structure-aware metrics:

- **Precision@K, NDCG@K**: Accuracy of top-ranked emerging trends.
- **Spread Coefficient**: Number of unique users and locations linked to each trend.
- **Embedding Drift**: Change in representation over time, $\|\mathbf{h}_i - \bar{\mathbf{h}}_i\|_2$.
- **Injected Trend Recall**: Fraction of synthetic ground-truth trends correctly recovered.

6.4 Results on Reddit-Food

Table 1 summarizes performance on the Reddit dataset. The proposed method outperforms all baselines in both ranking quality and structural coverage.

Figure 2 shows that the model captures meaningful and diverse temporal patterns in trend dynamics.

6.5 Results on Synthetic-Controlled Dataset

On synthetic data, our model achieves both high recall and low false positive rates, as shown in Table 2.

Table 1. Performance on Reddit-Food Dataset

Model	Prec@10	NDCG@20	Spread	Drift Score
KFB	0.55	0.59	3.2	0.41
PGD	0.61	0.65	3.7	0.48
S-HGNN	0.70	0.73	4.3	0.56
DGAT	0.71	0.75	4.6	0.57
HyperSAGNN	0.73	0.78	4.8	0.60
UniGNN-Hyper	0.74	0.79	4.9	0.61
AllSetTransformer	0.76	0.80	5.1	0.65
Proposed Model	**0.81**	**0.85**	**5.6**	**0.70**

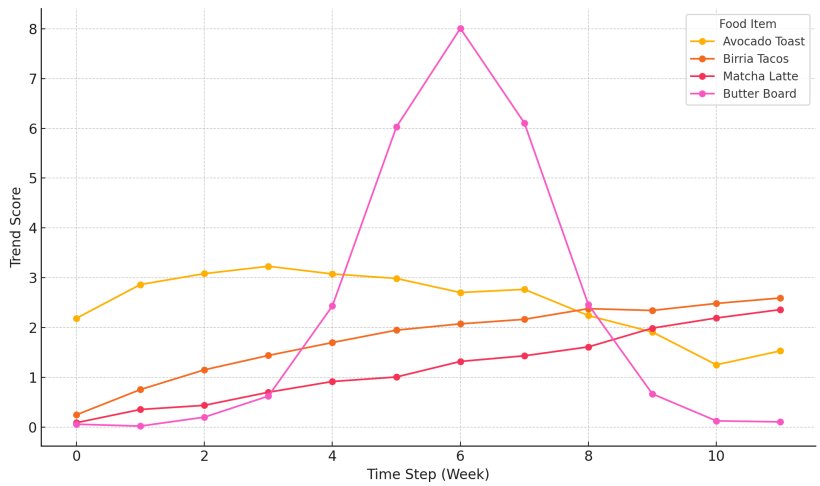

Fig. 2. Temporal trend scores for selected food items. The proposed method captures different temporal behaviors, including steady growth (e.g., Birria Tacos), gradual rise (e.g., Matcha Latte), and sudden spikes (e.g., Butter Board).

6.6 Embedding Drift and Semantic Novelty

We analyze the ability of the model to capture semantic change by visualizing how food item embeddings evolve over time.

As shown in Figure 3, the model captures semantic change, with emerging trends drifting away from their earlier representations. This supports the interpretability of the embedding drift term in the trend scoring function.

6.7 Ablation Study

We perform ablation experiments to isolate the contribution of individual components in the model. Table 3 shows how removing nodes or modeling features affects performance.

Table 2. Performance on Synthetic Dataset with Injected Trends

Model	Recall of Injected Trends	False Positive Rate
PGD	0.72	0.18
S-HGNN	0.79	0.14
HyperSAGNN	0.83	0.11
Proposed Model	**0.91**	**0.08**

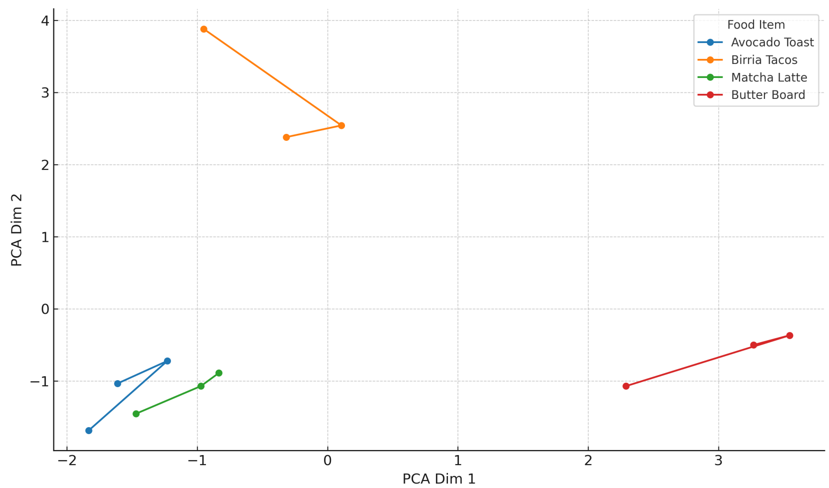

Fig. 3. Embedding trajectories for food items across three time steps using PCA. The spatial movement of points reflects semantic drift, as learned by the temporal hypergraph model.

Each modeling component contributes to the performance. Notably, user and location nodes are especially important for ranking accuracy, while temporal modeling and semantic drift terms improve interpretability.

6.8 Statistical Significance

We use paired t-tests over five randomized data splits to verify that the improvements over AllSetTransformer are statistically significant for both Precision@10 and NDCG@20 ($p < 0.01$).

7 Industrial Implications

The proposed framework provides a scalable and interpretable solution for trend detection in the food and beverage industry. By modeling complex, multi-entity interactions across time, it enables early identification of emerging food items, region-specific trends, and shifts in consumer discourse.

Table 3. Ablation on Hypergraph Components (Precision@10)

Model Variant	Prec@10	NDCG@20
Full Model	**0.81**	**0.85**
− Hashtag Nodes	0.75	0.78
− Location Nodes	0.76	0.79
− User Nodes	0.72	0.76
− Temporal Modeling	0.74	0.77
− Drift Score Term	0.73	0.75
Random Edge Rewiring	0.68	0.71

The trend scoring mechanism produces actionable signals that can assist product and operations teams in several ways. For example, restaurants and food brands can adjust menus proactively based on localized interest. Supply chain planners can anticipate demand fluctuations, while marketers can design campaigns around rising ingredients or dishes.

The modular design of the framework supports integration into existing analytics pipelines, including those used by food delivery platforms, social monitoring systems, or retail intelligence tools. In addition, interpretability features—such as temporal attention and embedding drift—make the results more transparent and explainable for domain experts.

While the framework is designed for food trend detection, its structure is general and can be adapted to other sectors where social trends evolve rapidly. Potential applications include fashion, consumer electronics, wellness products, and lifestyle services, where early detection of demand signals is equally important.

8 Conclusion and Future Work

This paper introduced a temporal hypergraph framework for detecting emerging food trends from social media data. By modeling high-order relationships and their evolution over time, the method addresses limitations of traditional graph- and keyword-based approaches. The framework demonstrated improved accuracy and interpretability on both real-world and synthetic datasets, and its modular components offer practical advantages for industrial deployment.

Future work includes incorporating multimodal content such as images and reviews, extending the framework to real-time streaming data, and evaluating generalization to multilingual and culturally diverse datasets. In addition, we plan to explore applications beyond the food domain, focusing on trend detection in consumer-driven sectors such as fashion, wellness, and entertainment.

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