Hybrid Recommender System: Recommending Restaurants to Users

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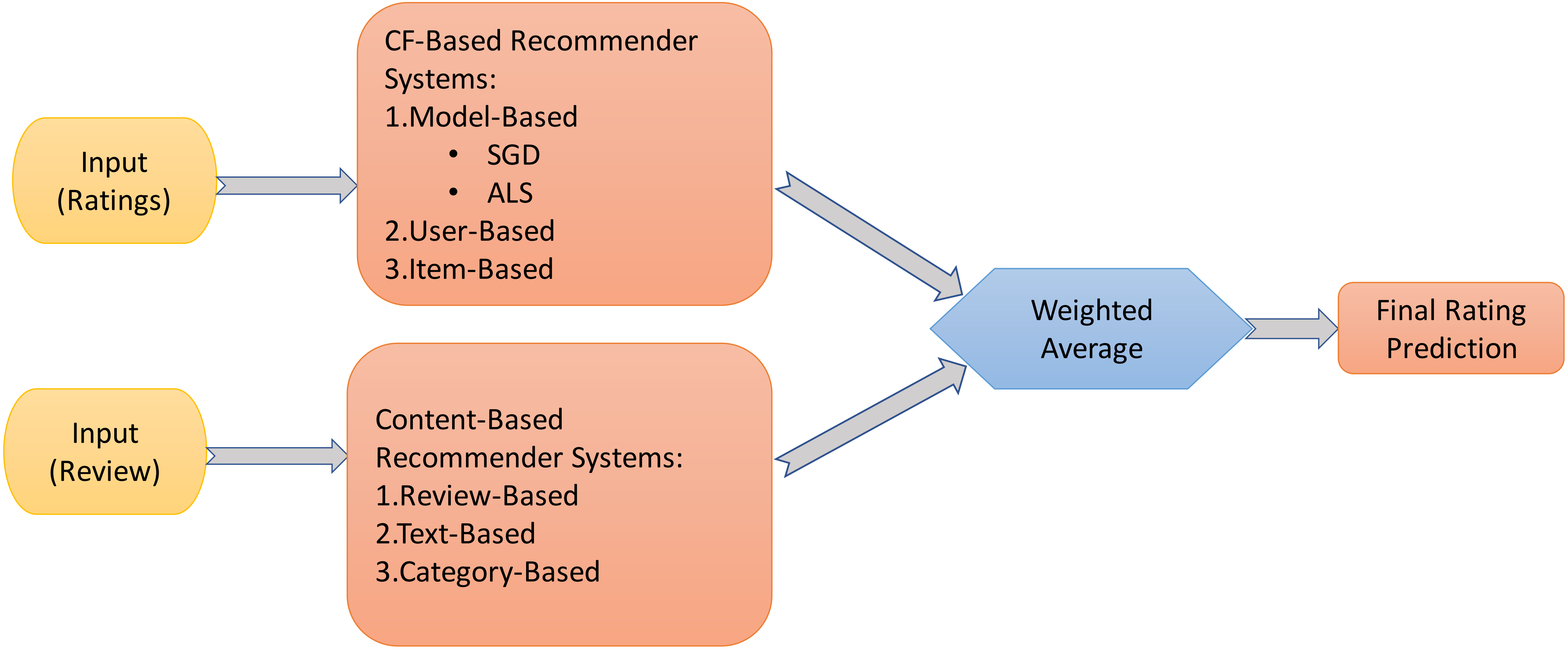
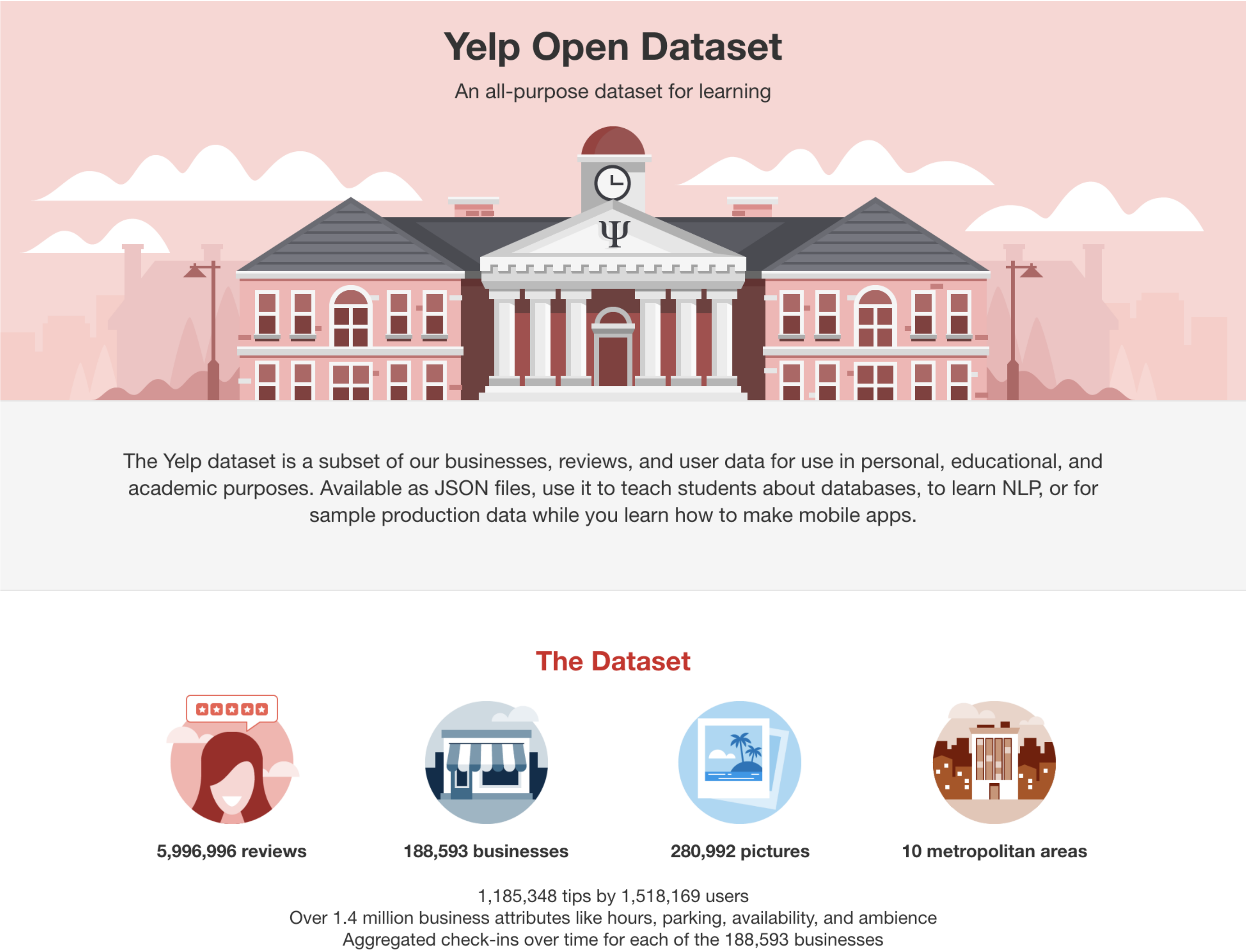
Hybrid-Model Predictions



Dataset

Pittsburgh
- 50,893 reviews
- 987 restaurants
- 3192 users
- Users > 20 reviews
- Faster testing and debugging

Las Vegas
- 158,880 reviews
- 8309 restaurants
- 5272 users
- Users > 50 reviews
- Proof of models built



Methodologies

Collaborative Filtering Based Models

- Model Based CF
  - Stochastic Gradient Descent (SGD)
  - Alternating Least Squares (ALS)
- User Based CF
- Item Based CF

Content Based Models

- Review based
- Text Based
- Category Based

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Model Based

Ratings Matrix: $X \in R^{U \times I}$

X

$5 \times 5\ matrix$

X_{11}	?	X_{13}	?	?
X_{21}	?	?	X_{24}	X_{25}
?	X_{32}	X_{33}	X_{34}	?
?	X_{42}	?	?	X_{45}
X_{51}	?	X_{53}	?	?

=

P

$3 \times 5\ matrix$

		a		
		b		
		c		

Q

$5 \times 3\ matrix$

e	f	g

$$X_{32} = (a, b, c).(e, f, g) = a * e + b * f + \mathrm{c} * \mathrm{g}$$

rating prediction

$$\hat{r}_{ui} = p_u^T q_i$$

item preference vector

user preference vector

Model Based

minimizing cost function

squared error: e

$$\min \sum_{(u,i)\in D} (r_{ui} - p_u^T q_i)^2 + \lambda(\|P\|^2 + \|Q\|^2)$$

known rating entries

regularization to prevent overfitting

Algorithms to minimize cost function

1. Stochastic Gradient Descent (SGD)

$$q_i = q_i + \alpha(2ep_u + \lambda q_i)$$
$$p_u = p_u + \alpha(2eq_i + \lambda p_u)$$

2. Alternating Least Squares (ALS)

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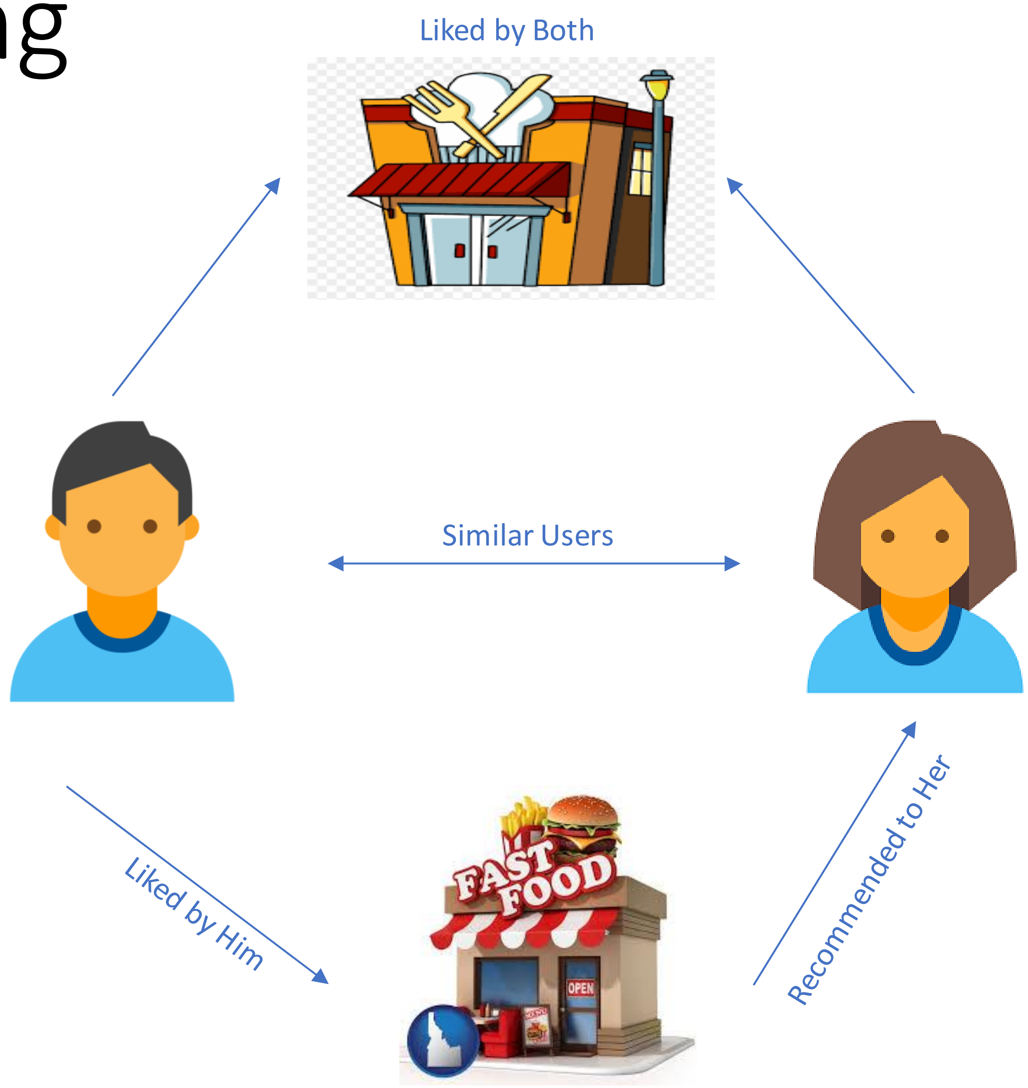
Collaborative-Filtering Based Models

- ## User-Based CF

  Focuses on taking people who have rated similarly to a user, and predicting rating depending upon how others have rated that item

- ## Item-Based CF

  Focuses on taking items which are similar to the given item, and predicting rating depending on those items ratings as given by the user



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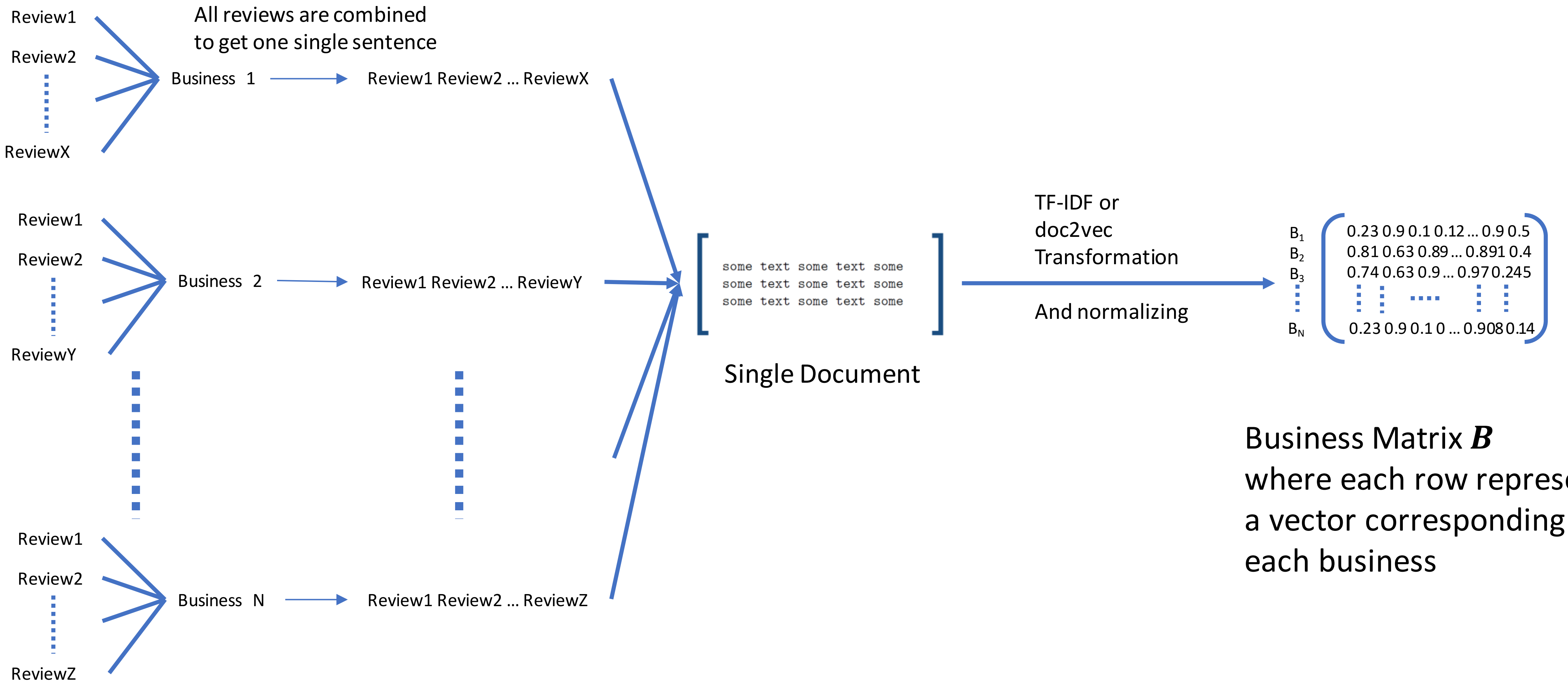
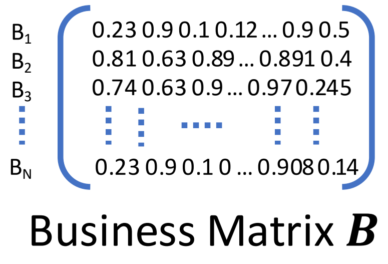
Review-Based Model

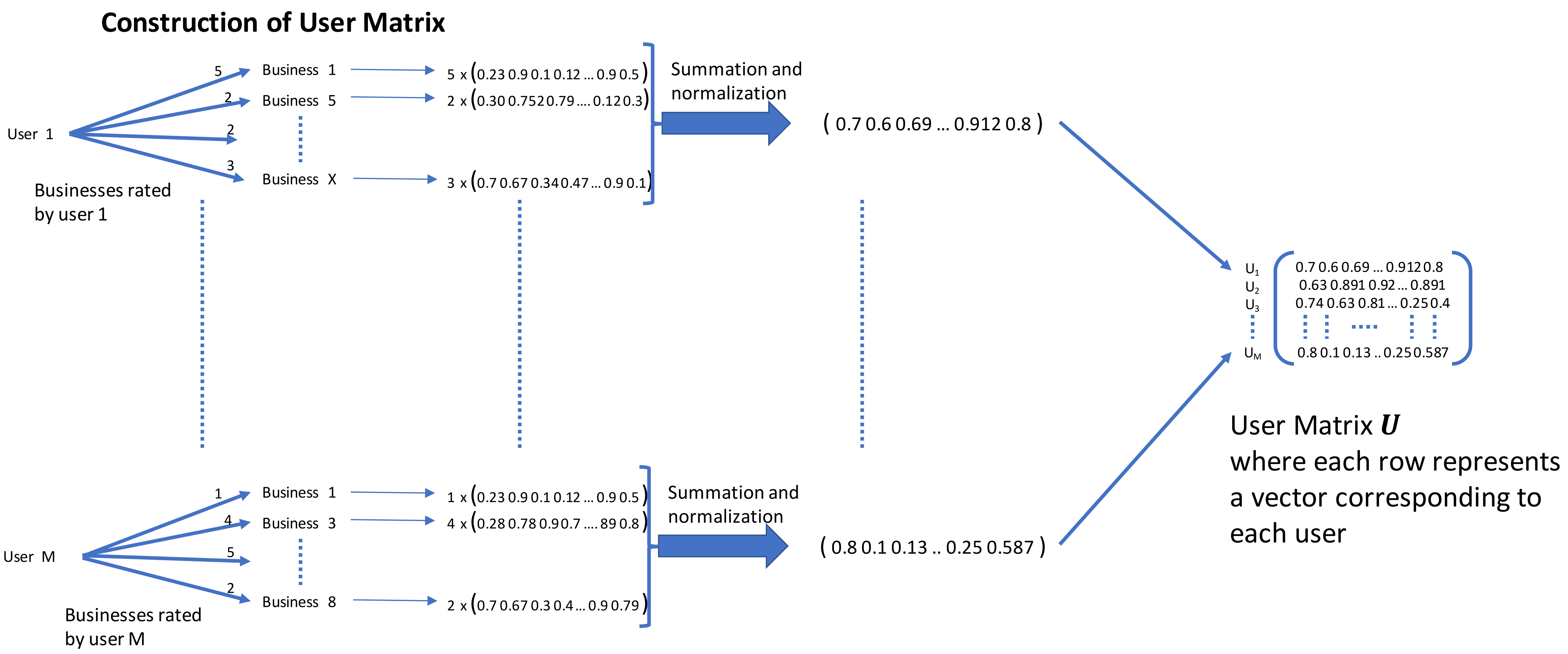
Construction of Business Matrix



Business Matrix $\boldsymbol{B}$
where each row represents
a vector corresponding to
each business

Review-Based Model





Review Based

- To compute the cosine similarity between a User and a Business we compute $S \in R^{I \times Q}$ (I unique Businesses and Q unique Users) by,

User Matrix

$$S = UB^{\mathrm{T}}$$

Similarity Matrix

Business Matrix

	B_1	B_2	B_3	B_4	B_5
U_1	-0.12	0.76	-0.56	0.33	0.36
U_2	0.37	0.21	0.45	0.36	-0.98
U_3	0.83	-0.25	.074	0.11	0.65
U_4	0.26	0.52	0.73	-0.84	0.36
U_5	-0.64	0.28	0.57	0.18	0.82

- To transform the similarity values (-1,1) into ratings (1,5) we build a regression model to regress ratings over similarity values.

Text-Based Model

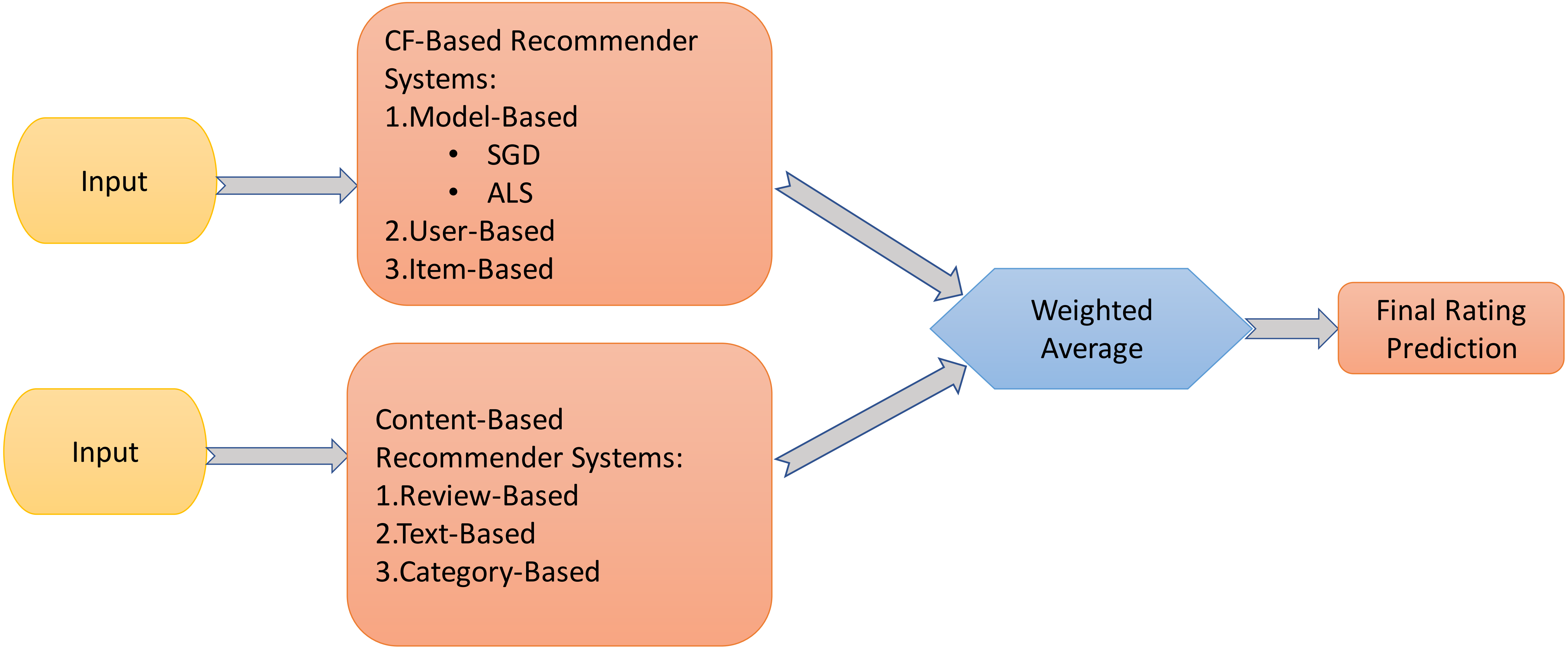
- We compute the Business Matrix B similar to Review-based Model we discussed earlier.
- Here we follow the similar approach to compute the User Matrix U as we did for the Business Matrix.
- Rest we follow the same procedure as in Review Based Model once we have User and Business Matrices.
- We compute the similarity matrix $S = UB^{\mathrm{T}}$, $S \in R^{I \times Q}$ and regress ratings over similarity values.

Category-Based Model

- This method is similar to Review-based Model with different input.
- In Review-based Model we used the review as the input here we use business specific information as features.

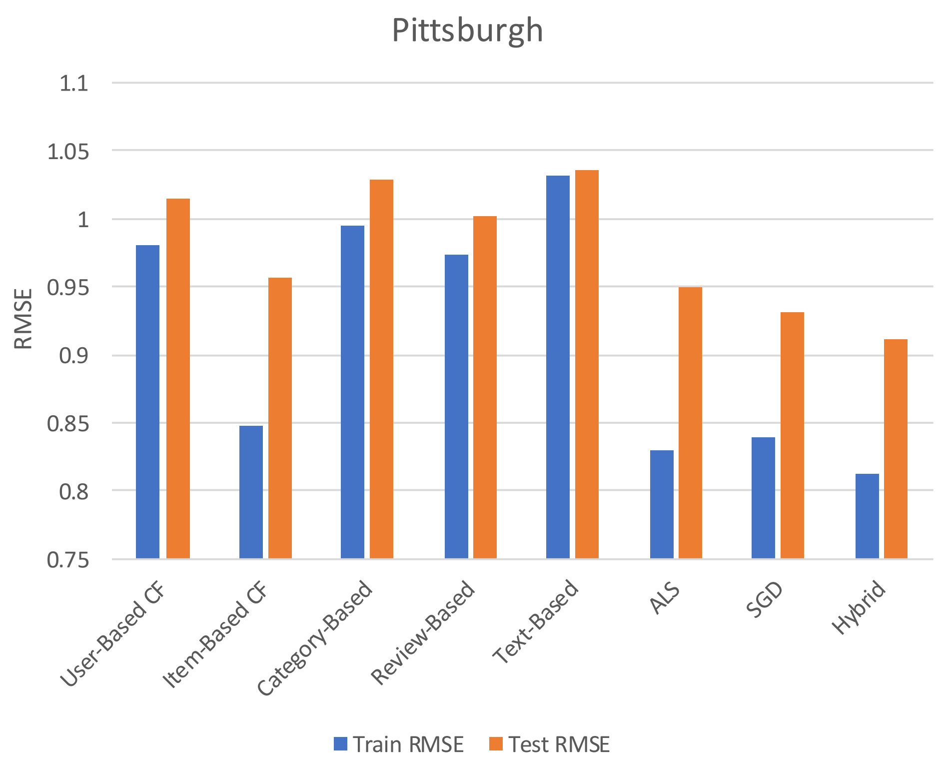
```
Old_string =
{ "attributes": {"BikeParking": "False",
"BusinessAcceptsCreditCards": "True",
"BusinessParking": "{'garage': False, 'street': True, 'validated': False, 'lot': False, 'valet': False}”,
 "NoiseLevel": "average",
"RestaurantsAttire": "casual",
"RestaurantsDelivery": "False",
"RestaurantsGoodForGroups": "True",
"RestaurantsPriceRange2": "2"
},
"categories": "Tours, Breweries, Pizza, Restaurants, Food, Hotels & Travel"
}

New_String = New_string =
businessacceptscreditcards businessparking_street noiselevel_average restaurantsattire_casual
restaurantsgoodforgroups restaurantspricerange2_2 tours breweries pizza restaurants food hotels travel
```

Hybrid-Model Predictions (RECAP)

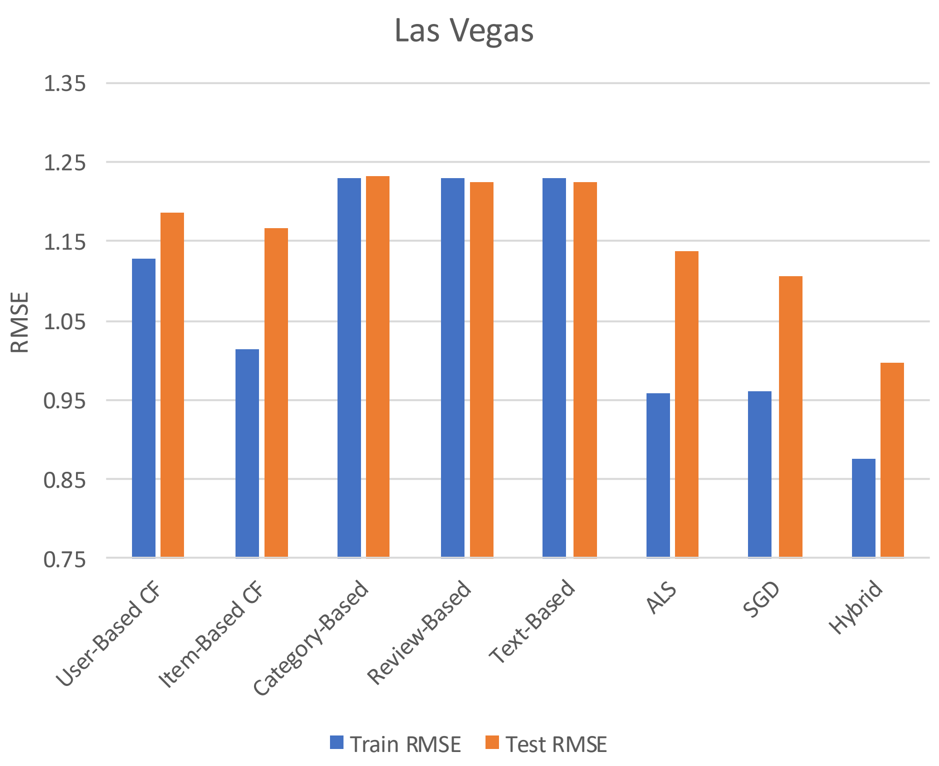


Results

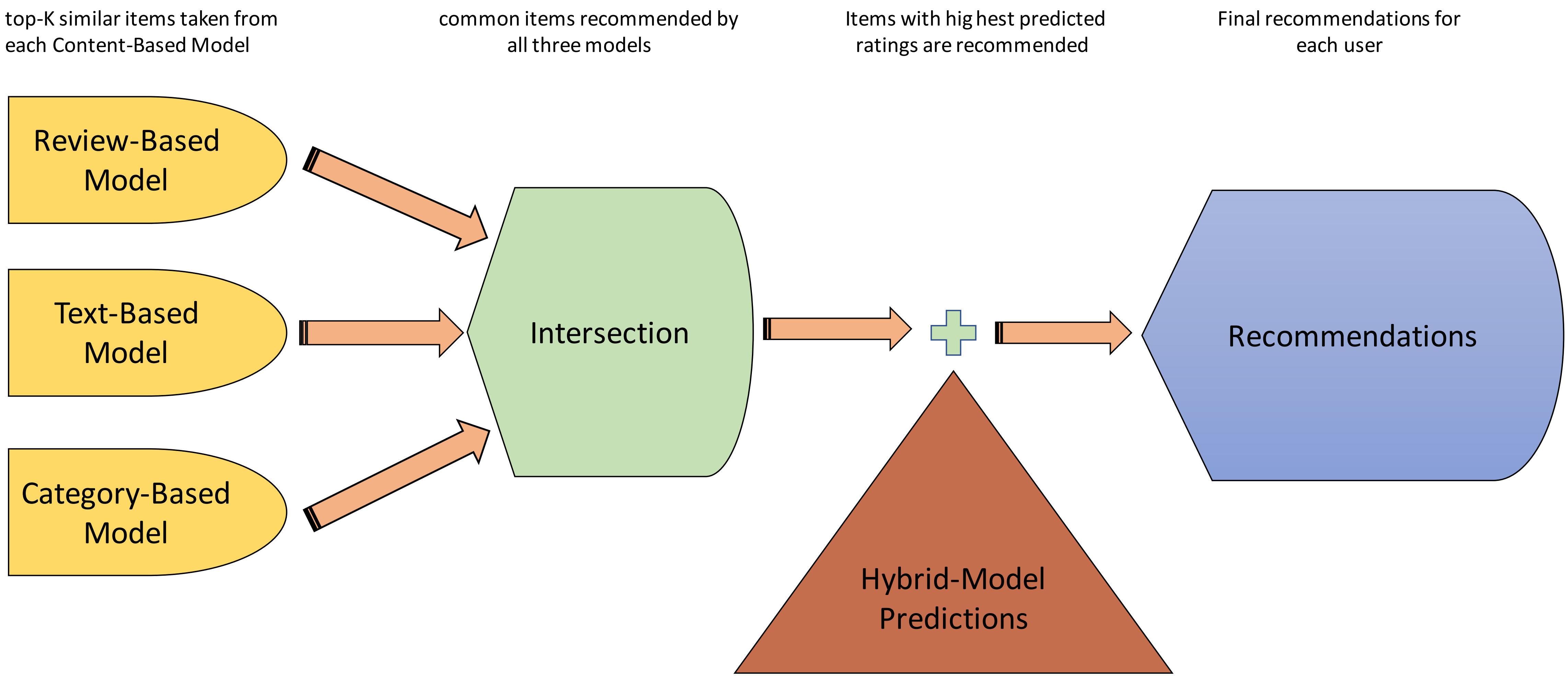
RMSEs for Pittsburgh



RMSEs for Las Vegas



Hybrid-Model Recommendations



Subjective Analysis

User Preferences

- Prefers Italian, pizza, or alcohol 67% of time
- Prefers price range of 1 or 2 (from 1-4) 98% of time
- Prefers restaurants who accept credit cards 100 % of time
- Prefer restaurants which are good for kids 70% of times
- Prefer restaurants with average noise level 65% of times

User Recommendations

- 80% of restaurants recommended served Italian, pizza, or alcohol
- 100% of restaurants recommended had price range of 1 or 2
- 100% of restaurants recommended accepted credit cards
- 65% of restaurants recommended were good for kids
- 70% of restaurants recommended have average noise level

Summary

- We implemented seven different models including 4 collaborative and 3 content based, combining them into a Hybrid Model.
- For each user, we predicted his/her rating for a restaurant as well as recommended them some restaurant that they might like.
- Finally, we analyzed that the recommendations made to each user by hybrid model were closely aligned with their preferences.

Thank You