A Tutorial on Wikimedia Visual Resources and its Application to Neural Visual Recommender Systems

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Attentive Collaborative Filtering: Multimedia Recommendation with Item- and Component-Level Attention

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Context

- Multimedia recommendation.
- Explicit feedback is not always available.
- Rely on implicit users interactions.

Key Insights

- Two levels of implicit feedback:
  - Item level
  - Component Level

- **Leverage (hierarchical) attention mechanism** to weight the importance of an item/component in each level.

Approach

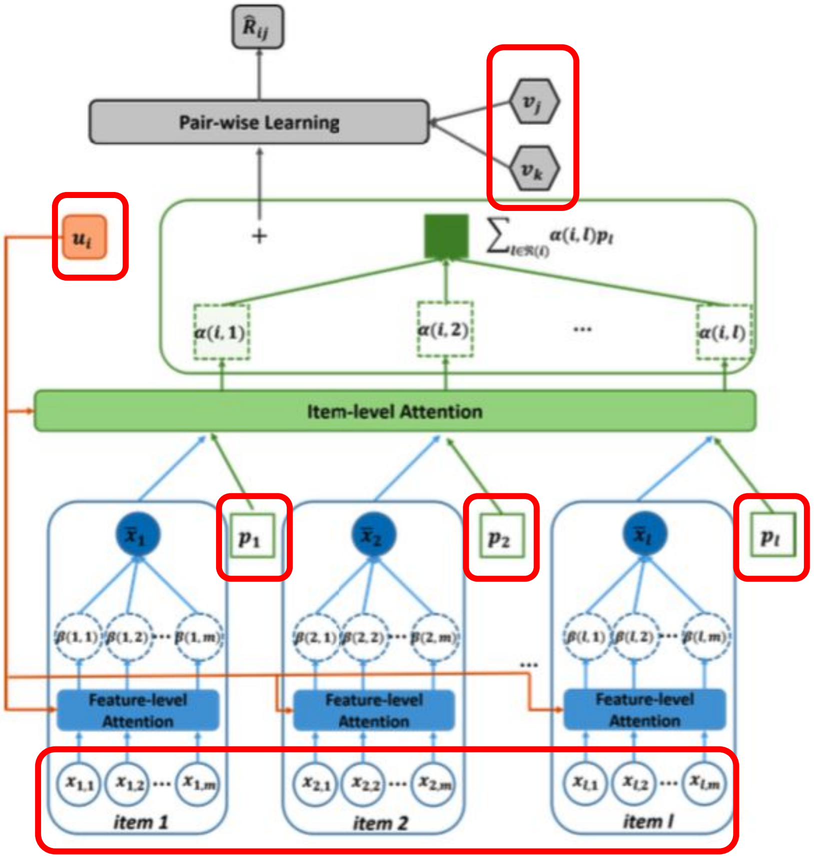
- BPR [4] based training.
- **Latent factor model + neighbourhood model.**
- Originally tested in Pinterest (images) and Vine (videos) datasets.
- In this tutorial we test it on the Wikimedia commons image dataset.

Model

- User *i*, parametrized as u_i
- Item *l*,*j*, parametrized as v_j & p_l
- Component *m* of item *l* x_{lm}

Implementation Detail:

$v_j = p_l$ was used for efficiency and better performance.



Model

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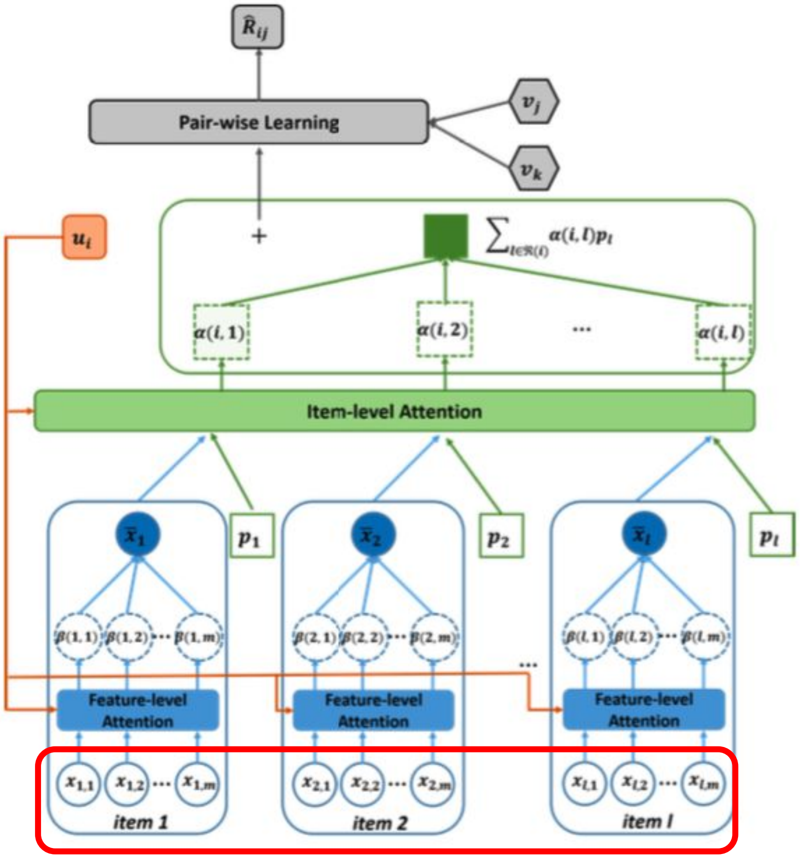


Model

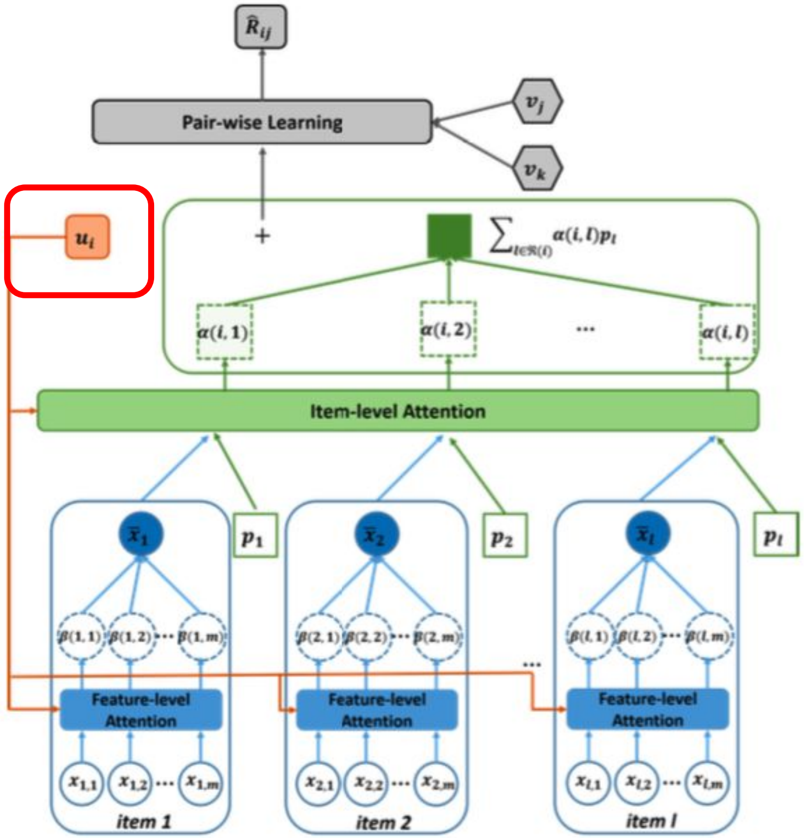
User representation

$$\boldsymbol{u}_i + \sum_{l \in \mathcal{R}(i)} \alpha(i,l)\boldsymbol{p}_l$$

Model

User representation

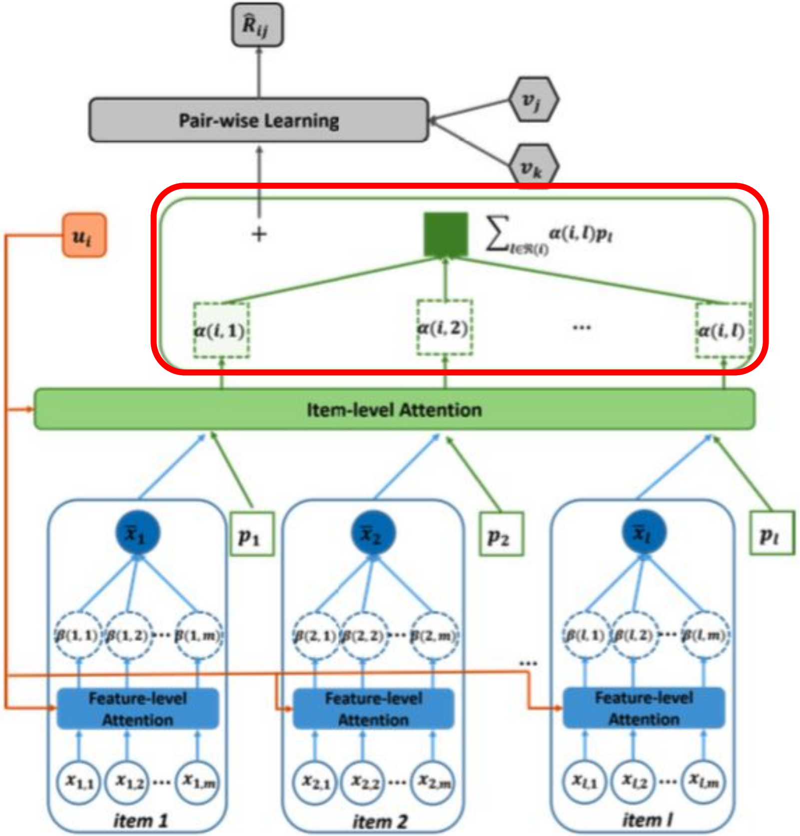
$$\boxed{\boldsymbol{u}_i} + \sum_{l \in \mathcal{R}(i)} \alpha(i,l)\boldsymbol{p}_l$$



Model

User representation

$$\boldsymbol{u}_i + \boxed{\sum_{l \in \mathcal{R}(i)} \alpha(i,l)\boldsymbol{p}_l}$$

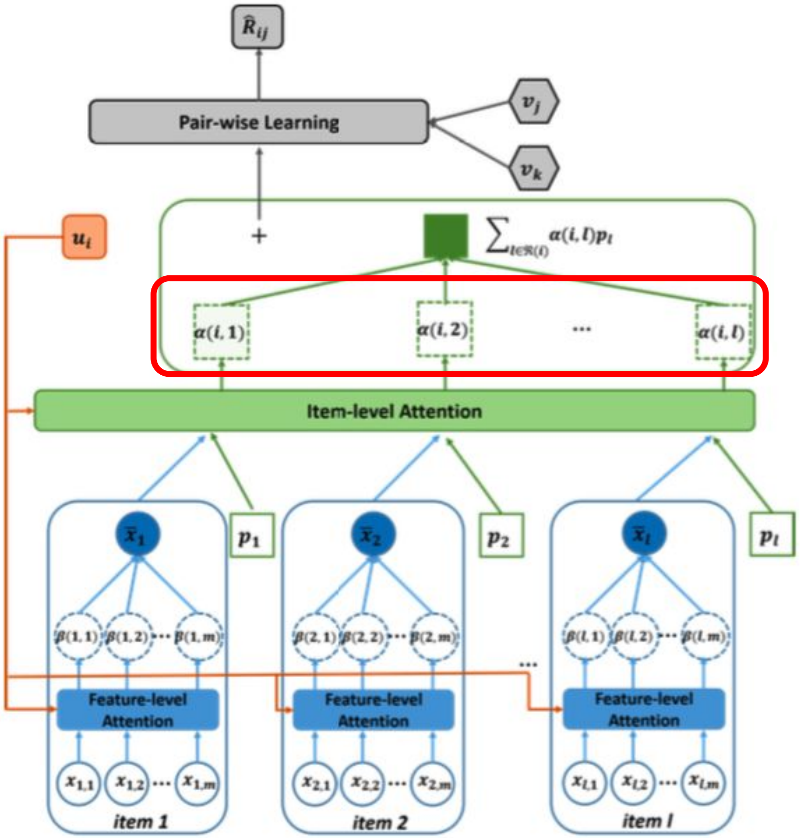


Model

User representation

item level attention

$$\boldsymbol{u}_i + \sum_{l\in\mathcal{R}(i)} \boxed{\alpha(i,l)}\,\boldsymbol{p}_l$$



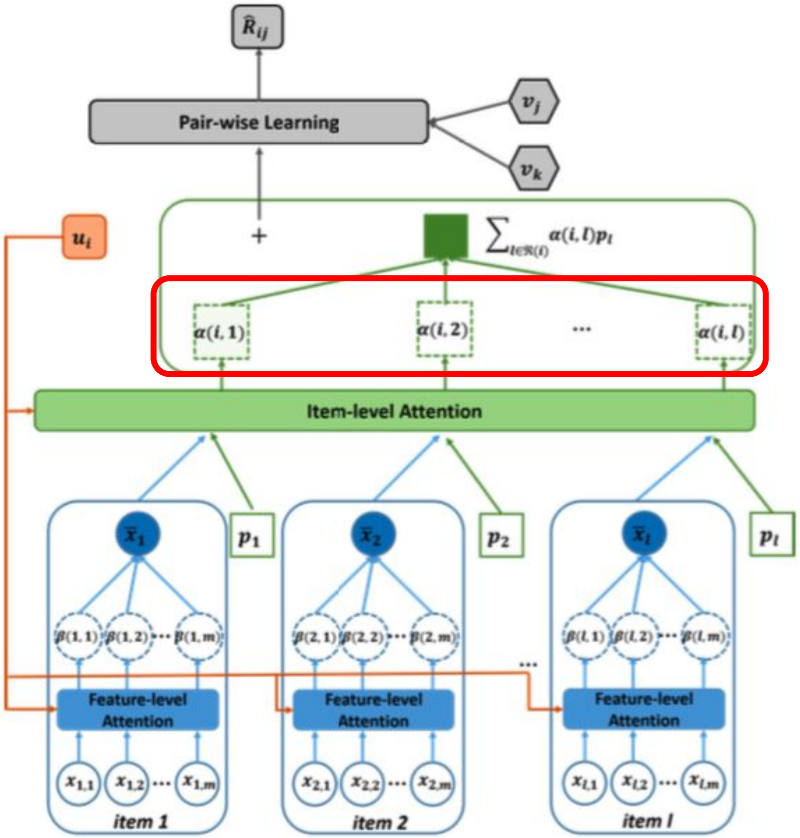
Model

User representation

$$\boldsymbol{u}_i + \sum_{\boxed{l \in \mathcal{R}(i)}} \alpha(i,l)\boldsymbol{p}_l$$

consumed item l by user i

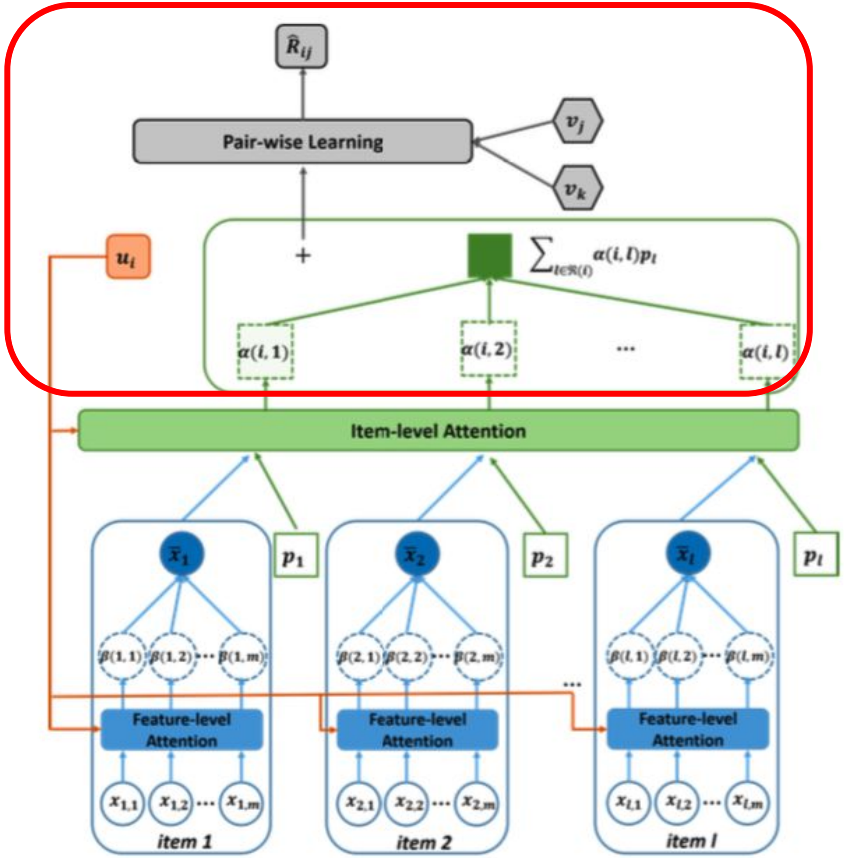
Implementation Detail: Limited the profile to a maximum of 9 items per user.



Model

Estimated score

$$\hat{R}_{ij} = \left(\boldsymbol{u}_i + \sum_{l \in \mathcal{R}(i)} \alpha(i,l)\boldsymbol{p}_l\right)^T \boldsymbol{v}_j$$



Model

User representation

$$\boldsymbol{u}_i + \sum_{l \in \mathcal{R}(i)} \alpha(i,l)\boldsymbol{p}_l$$

Estimated score

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Model

User representation

item level attention

$$\boldsymbol{u}_i + \sum_{l \in \mathcal{R}(i)} \alpha(i,l)\boldsymbol{p}_l$$

consumed item *l* by user *i*

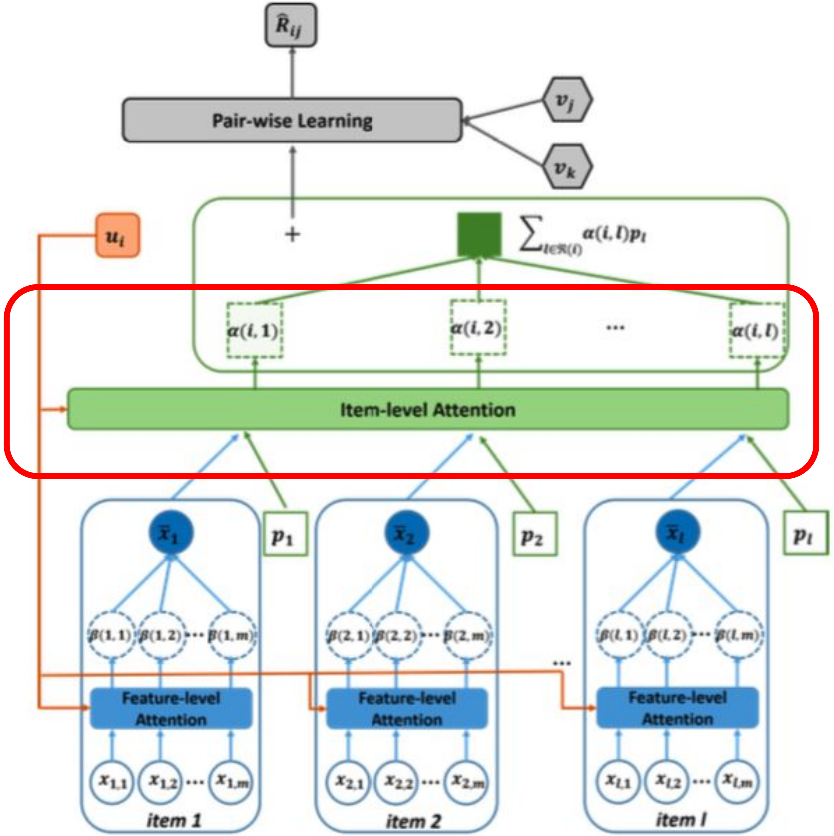
Estimated score

$$\hat{R}_{ij} = \left(\boldsymbol{u}_i + \sum_{l \in \mathcal{R}(i)} \alpha(i,l)\boldsymbol{p}_l \right)^T \boldsymbol{v}_j$$

Implementation Detail: Limited the profile to a maximum of 9 items per user.

Model

Item-level Attention



Item Level Attention

user's *i* factors

$$a(i,l) = \boldsymbol{w}_1^T \phi(\boldsymbol{W}_{1u} \boxed{\boldsymbol{u}_i} + \boldsymbol{W}_{1v}\boldsymbol{v}_l + \boldsymbol{W}_{1p}\boldsymbol{p}_l + \boldsymbol{W}_{1x}\bar{\boldsymbol{x}}_l + \boldsymbol{b}_1) + \boldsymbol{c}_1$$

Item Level Attention

$$a(i,l) = \boldsymbol{w}_1^T \phi(\boldsymbol{W}_{1u}\boldsymbol{u}_i + \boldsymbol{W}_{1v}\boxed{\boldsymbol{v}_l} + \boldsymbol{W}_{1p}\boxed{\boldsymbol{p}_l} + \boldsymbol{W}_{1x}\bar{\boldsymbol{x}}_l + \boldsymbol{b}_1) + \boldsymbol{c}_1$$

item's l factors

Item Level Attention

$$a(i,l) = \boldsymbol{w}_1^T \phi(\boldsymbol{W}_{1u}\boldsymbol{u}_i + \boldsymbol{W}_{1v}\boldsymbol{v}_l + \boldsymbol{W}_{1p}\cancel{\boldsymbol{p}_l} + \boldsymbol{W}_{1x}\bar{\boldsymbol{x}}_l + \boldsymbol{b}_1) + \boldsymbol{c}_1$$

item's *l* factors

Item Level Attention

item's l weighted components

$$a(i,l) = \boldsymbol{w}_1^T \phi(\boldsymbol{W}_{1u}\boldsymbol{u}_i + \boldsymbol{W}_{1v}\boldsymbol{v}_l + \boldsymbol{W}_{1p}\boldsymbol{p}_l + \boldsymbol{W}_{1x}\boxed{\bar{\boldsymbol{x}}_l} + \boldsymbol{b}_1) + \boldsymbol{c}_1$$

Item Level Attention

$$a(i,l) = \boldsymbol{w}_1^T \boxed{\phi}(\boldsymbol{W}_{1u}\boldsymbol{u}_i + \boldsymbol{W}_{1v}\boldsymbol{v}_l + \boldsymbol{W}_{1p}\boldsymbol{p}_l + \boldsymbol{W}_{1x}\bar{\boldsymbol{x}}_l + \boxed{\boldsymbol{b}_1}) + \boxed{\boldsymbol{c}_1}$$

ReLu

bias terms

Item Level Attention

$$a(i,l) = \boldsymbol{w}_1^T \phi(\boldsymbol{W}_{1u}\boldsymbol{u}_i + \boldsymbol{W}_{1v}\boldsymbol{v}_l + \boldsymbol{W}_{1p}\boldsymbol{p}_l + \boldsymbol{W}_{1x}\bar{\boldsymbol{x}}_l + \boldsymbol{b}_1) + \boldsymbol{c}_1$$

Item Level Attention

It’s an attention after all

$$\alpha(i,l) = \frac{\exp\left(a(i,l)\right)}{\sum_{n \in \mathcal{R}(i)} \exp\left(a(i,n)\right)}$$

Item Level Attention

user's *i* factors

item's *l* weighted components

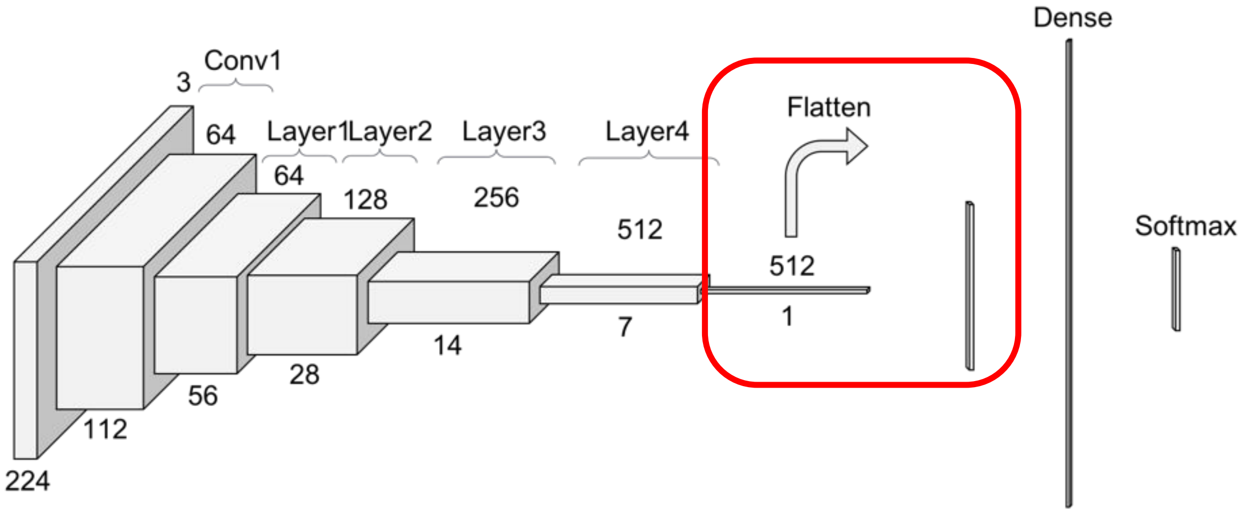
$$a(i,l) = \mathbf{w}_1^T \phi(\mathbf{W}_{1u}\mathbf{u}_i + \mathbf{W}_{1v}\mathbf{v}_l + \mathbf{W}_{1p}\mathbf{p}_l + \mathbf{W}_{1x}\overline{\mathbf{x}}_l + \mathbf{b}_1) + \mathbf{c}_1.$$

item's *l* factors

bias terms

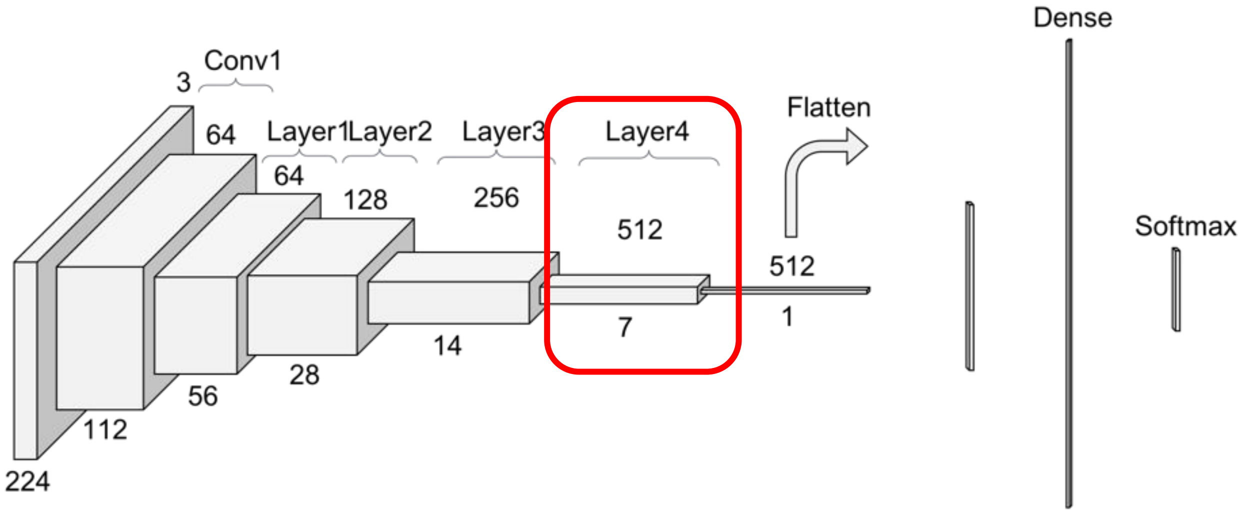
$$\alpha(i,l) = \frac{exp\,(a(i,l))}{\sum_{n\in\mathcal{R}(i)} exp\,(a(i,n))}.$$

Components



Dense
Conv1
3
64
Layer1Layer2
Layer3
Layer4
Flatten
64
128
256
512
512
Softmax
1
7
14
28
56
112
224

Components



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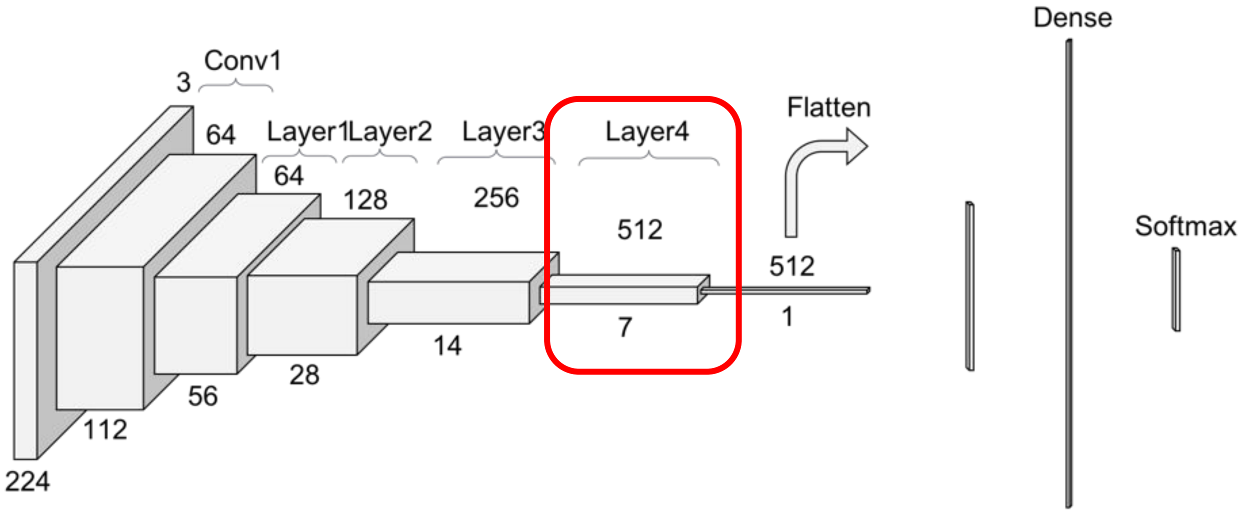


Implementation detail:

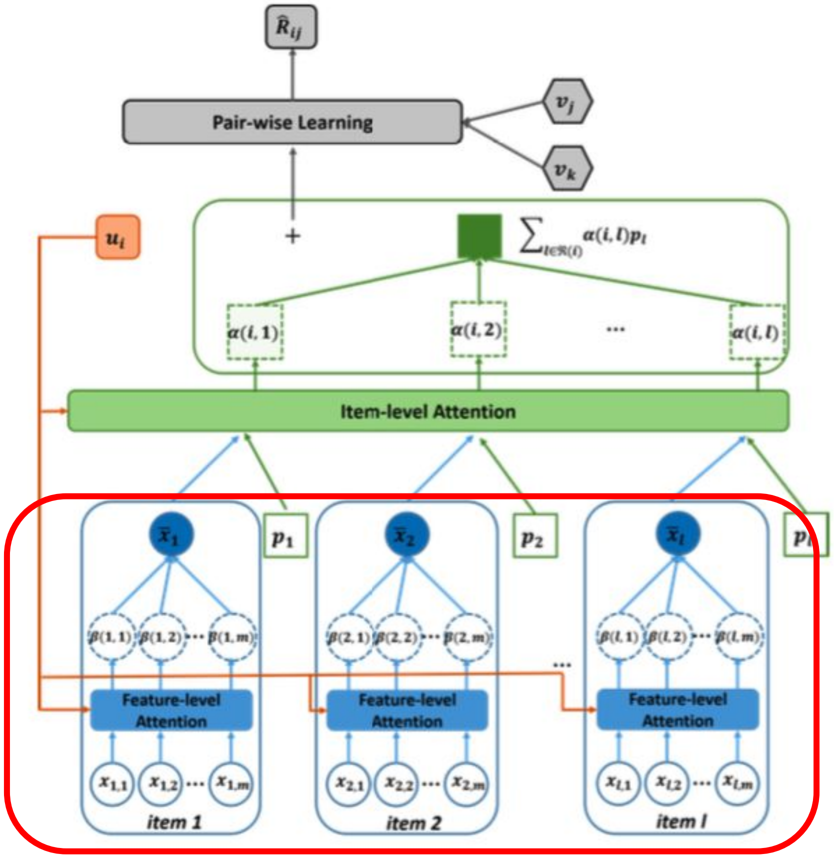
Used the output of the ***layer4*** of a ResNet50 [2] for this tutorial.

Add layer to reduce dimension of each feature vector.

Model

Weighted components for item *l*

$$\bar{\boldsymbol{x}}_l = \sum_{m=1}^{|\{x_{l*}\}|} \beta(i,l,m) \cdot x_{lm}$$

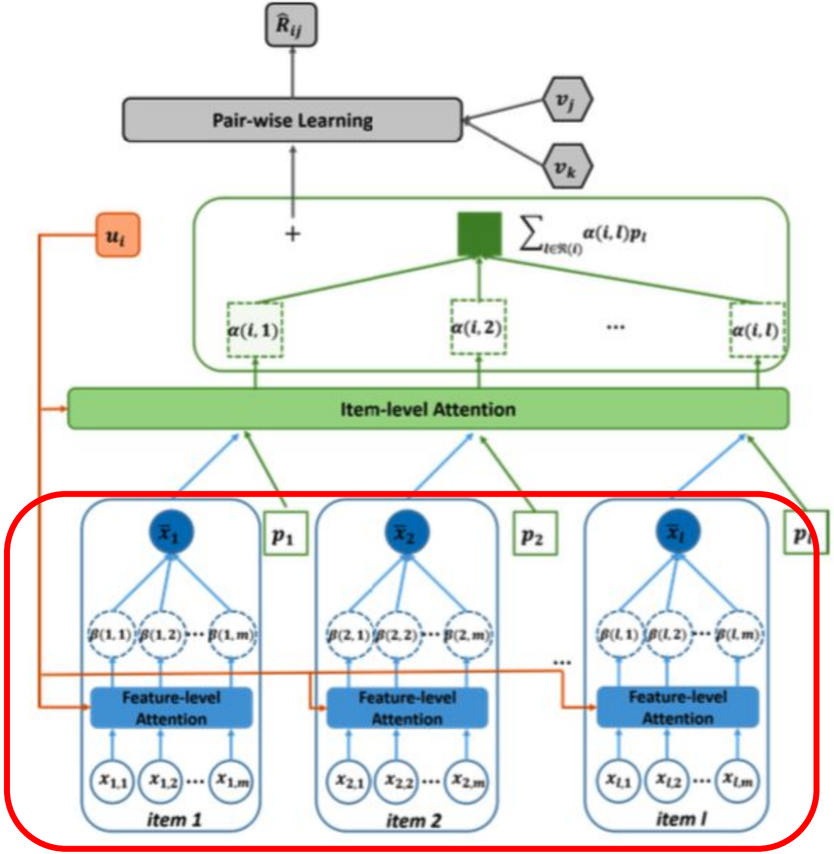


Model

Weighted components for item *l*

$$\bar{\boldsymbol{x}}_l = \sum_{m=1}^{|\{x_{l*}\}|} \beta(i,l,m) \cdot \boxed{x_{lm}}$$

component features

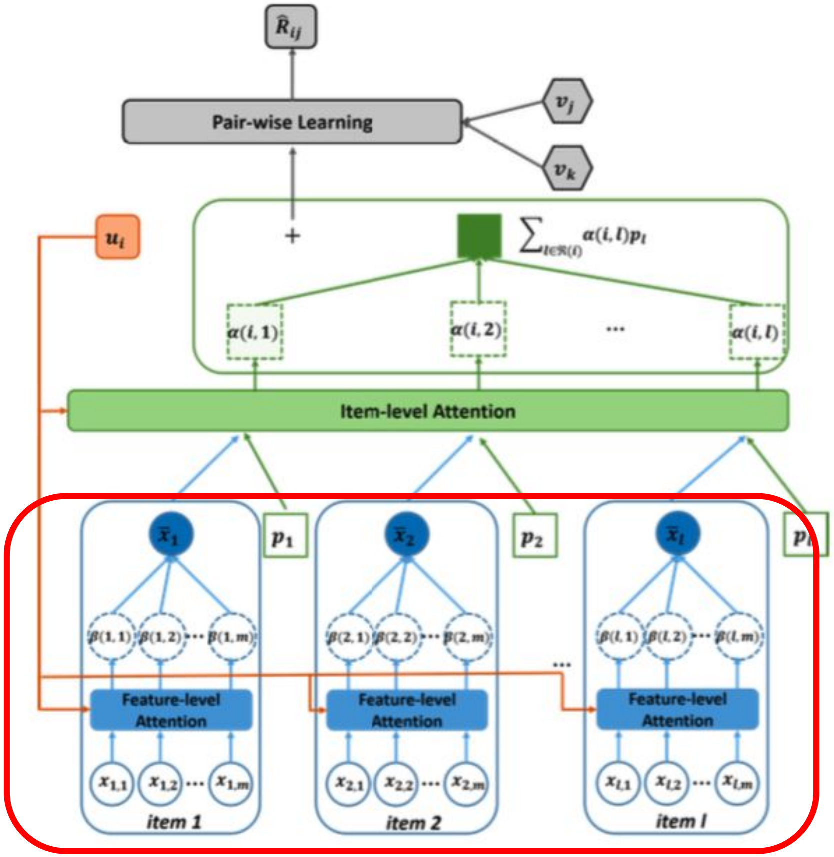


Model

Weighted components for item *l*

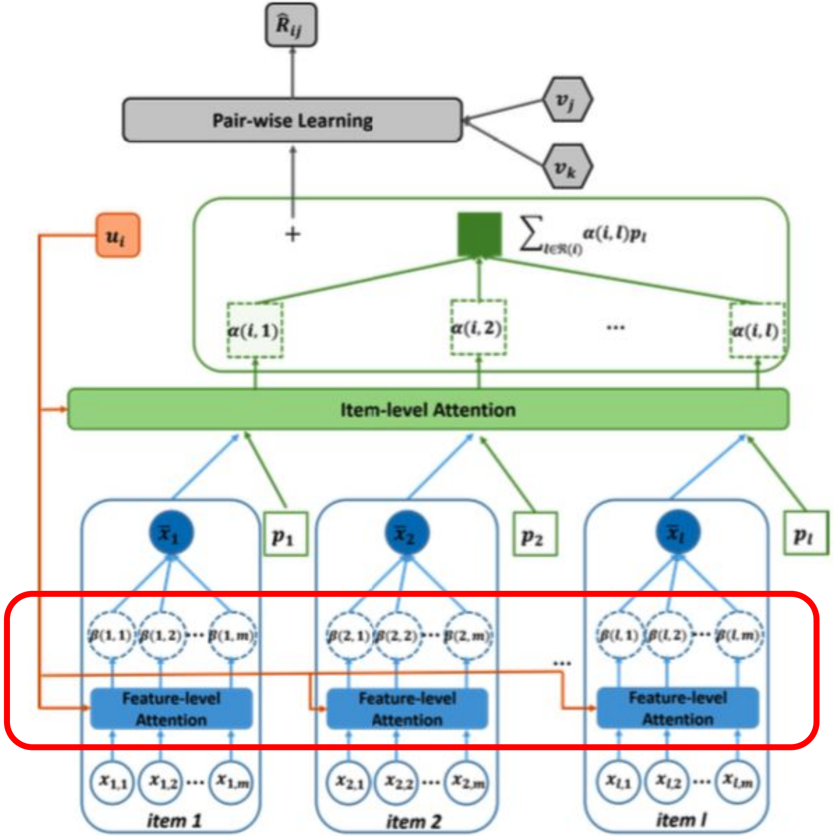
$$\bar{\boldsymbol{x}}_l = \sum_{m=1}^{|\{x_{l*}\}|} \boxed{\beta(i,l,m)} \cdot x_{lm}$$

component level attention



Model

Component-level Attention



Component Level Attention

user's *i* factors

$$b(i,l,m) = \boldsymbol{w}_2^T \phi(\boldsymbol{W}_{2u} \boxed{\boldsymbol{u}_i} + \boldsymbol{W}_{2x} \boldsymbol{x}_{lm} + \boldsymbol{b}_2) + \boldsymbol{c}_2$$

Component Level Attention

$$b(i, l, m) = \boldsymbol{w}_2^T \phi(\boldsymbol{W}_{2u} \boldsymbol{u}_i + \boldsymbol{W}_{2x} \boxed{\boldsymbol{x}_{lm}} + \boldsymbol{b}_2) + \boldsymbol{c}_2$$

component *m* of item *l*

Component Level Attention

bias terms

$$b(i,l,m) = \boldsymbol{w}_2^T \boxed{\phi(} \boldsymbol{W}_{2u}\boldsymbol{u}_i + \boldsymbol{W}_{2x}\boldsymbol{x}_{lm} + \boxed{\boldsymbol{b}_2}) + \boxed{\boldsymbol{c}_2}$$

ReLU

Component Level Attention

$$b(i,l,m) = \boldsymbol{w}_2^T \boxed{\phi(}\boldsymbol{W}_{2u}\boldsymbol{u}_i + \boldsymbol{W}_{2x}\boldsymbol{x}_{lm} + \boldsymbol{b}_2) + \boldsymbol{c}_2$$

ReLU

Component Level Attention

It’s an attention after all

$$\beta(i,l,m) = \frac{\exp\left(b(i,l,m)\right)}{\sum_{n=1}^{|\{x_{l*}\}|} \exp\left(b(i,l,n)\right)}$$

Component Level Attention

Weighted components for item *l*

component level attention

$$\bar{\mathbf{x}}_l = \sum_{m=1}^{|\{\mathbf{x}_{l*}\}|} \beta(i, l, m) \cdot \mathbf{x}_{lm},$$

user's *i* factors

bias terms

$$b(i, l, m) = \mathbf{w}_2^T \phi(\mathbf{W}_{2u}\mathbf{u}_i + \mathbf{W}_{2x}\mathbf{x}_{lm} + \mathbf{b}_2) + \mathbf{c}_2,$$

ReLU

component *m* of item *l*

Training

BPR [4] Optimization Objective

$$\arg\min_{\boldsymbol{U},\boldsymbol{V}} \sum_{(i,j,k)\in\mathcal{R}_{\mathcal{B}}} -\ln\sigma(\hat{R}_{ij} - \hat{R}_{ik}) + \lambda(||\boldsymbol{U}^2|| + ||\boldsymbol{V}^2||)$$

Trained using Adam.

Implementation detail:

Regularization was key to increase performance as well as to avoid flat attentions.

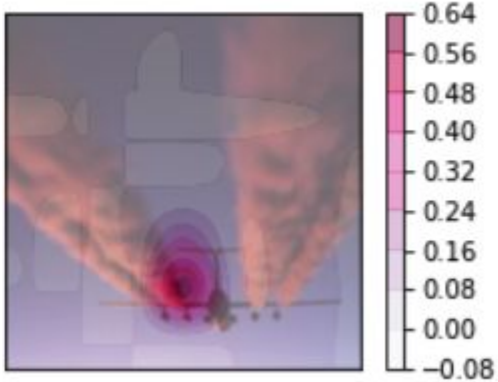
$0 < \lambda < 10^{-4}$ worked, with 10^{-5} achieving the best results.

Main Results

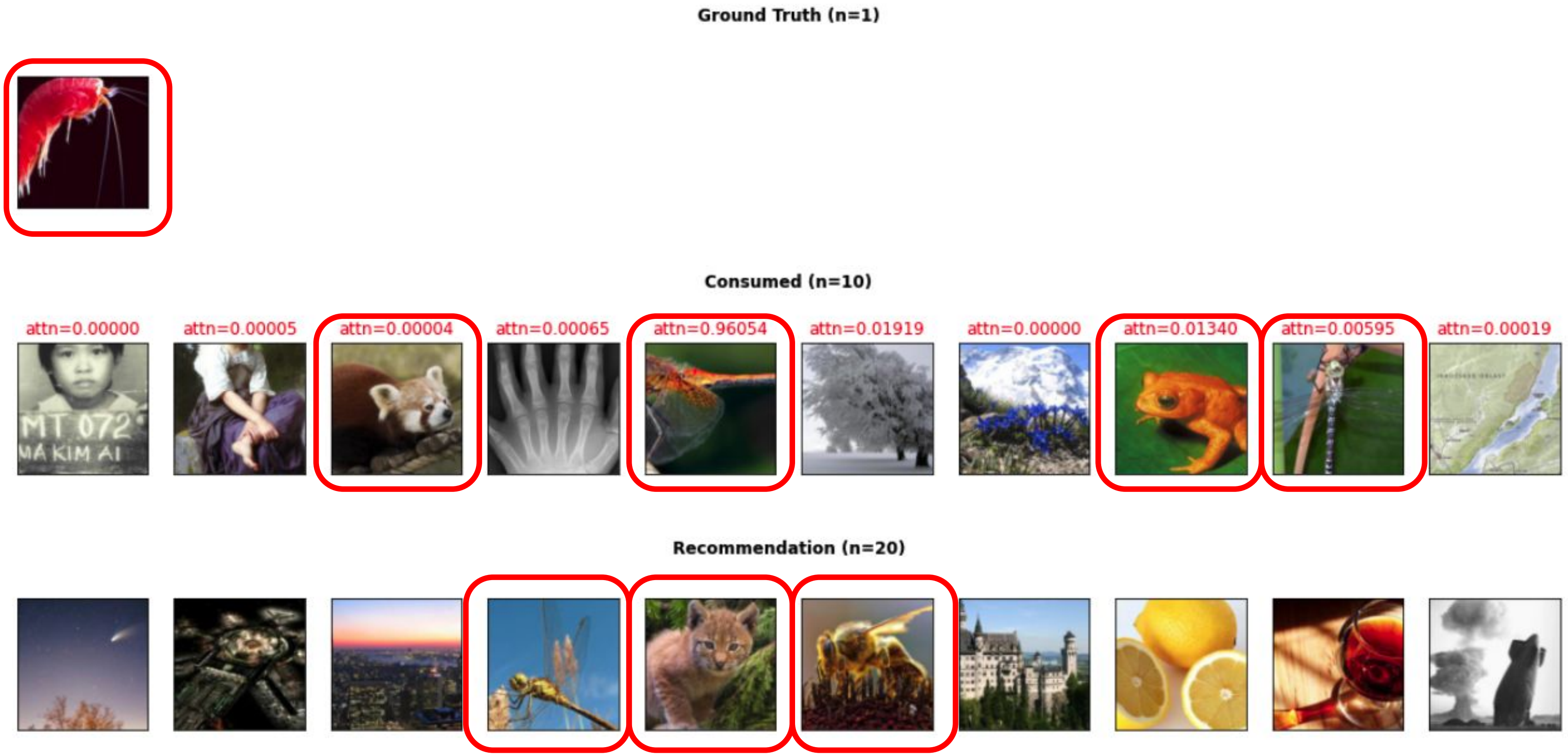
AUC	RR	R@20	P@20	nDCG@20	R@100	P@100	nDCG@100
0.77703	0.03548	0.01381	0.00802	0.04792	0.05142	0.00588	0.07886

Recommendation Examples

Attention Visualization



Recommendation Examples



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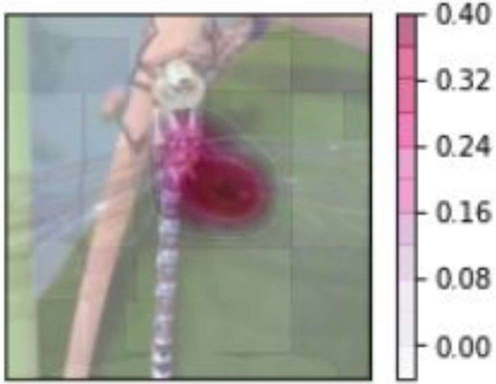

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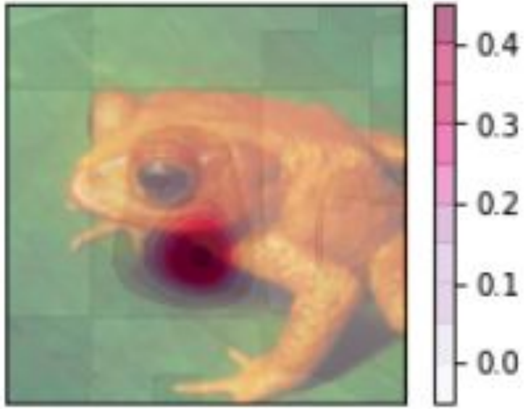

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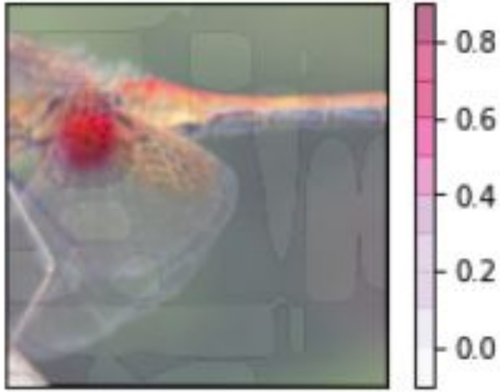
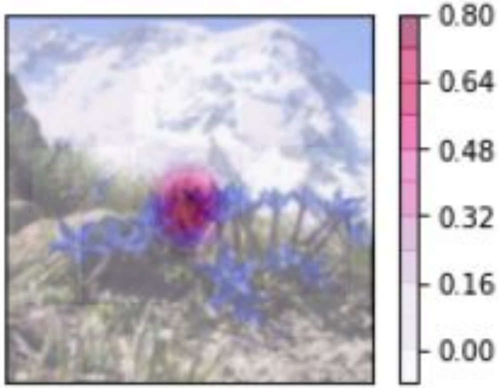


Attention Visualization



Attention Visualization

VisRec: A Hands-on Tutorial on Deep Learning for Visual Recommender Systems

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Thank you!

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References

[1] Chen, J., Zhang, H., He, X., Nie, L., Liu, W., & Chua, T. S. (2017, August). Attentive collaborative filtering: Multimedia recommendation with item-and component-level attention. In *Proceedings of the 40th International ACM SIGIR conference on Research and Development in Information Retrieval* (pp. 335-344).

[2] Melinte, D. O., & Vladareanu, L. (2020). Facial Expressions Recognition for Human–Robot Interaction Using Deep Convolutional Neural Networks with Rectified Adam Optimizer. Sensors, 20(8), 2393.

[3] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).

[4] S. Rendle, C. Freudenthaler, Z. Gantner, and L. Schmidt-Thieme. BPR: bayesian personalized ranking from implicit feedback. In UAI, pages 452–461. IEEE, 2009.

[5] Weston, J., Bengio, S., & Usunier, N. (2011). Wsabie: Scaling up to large vocabulary image annotation.

Supporting Material

General Implementation Details

Implemented using python 3.7.5 and pytorch 1.7.

Ran in research group cluster with 8-cpu and 2 GeForce GTX 1080 Ti (only one used per model training).

Each epoch took around 3 hours.

Algorithm

Input: User-item interaction matrix $\mathbf{R}$. Each item l is represented by a set of component features $\{x_{l*}\}$.

Output: Latent feature matrix $\mathbf{U}, \mathbf{V}, \mathbf{P}$ and parameters in attention model Θ

Initialize $\mathbf{U}$, $\mathbf{V}$ and $\mathbf{P}$ with Gaussian distribution. Initialize Θ with xavier [17].

repeat

  draw (i, j, k) from $\mathcal{R}_B$

  For each item l in $\mathcal{R}(i)$:

    For each component m in $\{\mathbf{x}_{l*}\}$:

      Compute $\beta(i, l, m)$ according to Eqns. (10) and (11)

    Compute $\overline{\mathbf{x}}_l$ according to Eqn. (12)

  Compute $\alpha(i, l)$ according to Eqns. (8) and (9)

  $\mathbf{u}_i' \leftarrow \mathbf{u}_i + \sum_{l \in \mathcal{R}(i)} \alpha(i, l)\mathbf{p}_l$

  $\hat{R}_{ijk} \leftarrow \mathbf{u}_i'\mathbf{v}_j - \mathbf{u}_i'\mathbf{v}_k$

  For each parameter θ in $\{\mathbf{U}, \mathbf{V}, \mathbf{P}, \Theta\}$:

    Update $\theta \leftarrow \theta + \eta \cdot \left(\frac{\exp^{-\hat{R}_{ijk}}}{1+\exp^{-\hat{R}_{ijk}}} \cdot \frac{\partial \hat{R}_{ijk}}{\partial \theta} + \lambda \cdot \theta\right)$.

until convergence

return $\mathbf{U}, \mathbf{V}, \mathbf{P}$ and Θ.

Algorithm

Input: User-item interaction matrix $\mathbf{R}$. Each item l is represented by a set of component features $\{x_{l*}\}$.

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  For each parameter θ in $\{\mathbf{U}, \mathbf{V}, \mathbf{P}, \Theta\}$:

    Update $\theta \leftarrow \theta + \eta \cdot \left(\frac{\exp^{-\hat{R}_{ijk}}}{1+\exp^{-\hat{R}_{ijk}}} \cdot \frac{\partial \hat{R}_{ijk}}{\partial \theta} + \lambda \cdot \theta\right).$

until convergence

return $\mathbf{U}$, $\mathbf{V}$, $\mathbf{P}$ and Θ.

Kaiming was used

Algorithm

Input: User-item interaction matrix $\mathbf{R}$. Each item l is represented by a set of component features $\{x_{l*}\}$.

Output: Latent feature matrix $\mathbf{U}$, $\mathbf{V}$, $\mathbf{P}$ and parameters in attention model Θ

Initialize $\mathbf{U}$, $\mathbf{V}$ and $\mathbf{P}$ with Gaussian distribution. Initialize Θ with xavier [17].

repeat

  draw (i, j, k) from $\mathcal{R}_B$

  For each item l in $\mathcal{R}(i)$:

    For each component m in $\{\mathbf{x}_{l*}\}$:

      Compute $\beta(i, l, m)$ according to Eqns. (10) and (11)

    Compute $\overline{\mathbf{x}}_l$ according to Eqn. (12)

  Compute $\alpha(i, l)$ according to Eqns. (8) and (9)

  $\mathbf{u}'_i \leftarrow \mathbf{u}_i + \sum_{l \in \mathcal{R}(i)} \alpha(i, l)\mathbf{p}_l$

  $\hat{R}_{ijk} \leftarrow \mathbf{u}'_i \mathbf{v}_j - \mathbf{u}'_i \mathbf{v}_k$

  For each parameter θ in $\{\mathbf{U}, \mathbf{V}, \mathbf{P}, \Theta\}$:

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until convergence

return $\mathbf{U}$, $\mathbf{V}$, $\mathbf{P}$ and Θ.

Triplet sampling originally bootstrap sampling, we did it without replacement for consistency.

Algorithm

Input: User-item interaction matrix $\mathbf{R}$. Each item l is represented by a set of component features $\{x_{l*}\}$.

Output: Latent feature matrix $\mathbf{U}$, $\mathbf{V}$, $\mathbf{P}$ and parameters in attention model Θ

Initialize $\mathbf{U}$, $\mathbf{V}$ and $\mathbf{P}$ with Gaussian distribution. Initialize Θ with xavier [17].
repeat
  draw (i, j, k) from $\mathcal{R}_B$
  For each item l in $\mathcal{R}(i)$:
    For each component m in $\{\mathbf{x}_{l*}\}$:
      Compute $\beta(i, l, m)$ according to Eqns. (10) and (11)
    Compute $\overline{\mathbf{x}}_l$ according to Eqn. (12)
  Compute $\alpha(i, l)$ according to Eqns. (8) and (9)
  $\mathbf{u}'_i \leftarrow \mathbf{u}_i + \sum_{l \in \mathcal{R}(i)} \alpha(i, l)\mathbf{p}_l$
  $\hat{R}_{ijk} \leftarrow \mathbf{u}'_i \mathbf{v}_j - \mathbf{u}'_i \mathbf{v}_k$
  For each parameter θ in $\{\mathbf{U}, \mathbf{V}, \mathbf{P}, \Theta\}$:
    Update $\theta \leftarrow \theta + \eta \cdot \left(\frac{\exp^{-\hat{R}_{ijk}}}{1+\exp^{-\hat{R}_{ijk}}} \cdot \frac{\partial \hat{R}_{ijk}}{\partial \theta} + \lambda \cdot \theta\right)$.
until convergence
return $\mathbf{U}$, $\mathbf{V}$, $\mathbf{P}$ and Θ.

Component attention

Algorithm

Input: User-item interaction matrix **R**. Each item l is represented by a set of component features $\{x_{l*}\}$.

Output: Latent feature matrix **U**, **V**, **P** and parameters in attention model Θ

1: Initialize **U**, **V** and **P** with Gaussian distribution. Initialize Θ with xavier [17].
2: **repeat**
3: draw (i, j, k) from $\mathcal{R}_B$
4: For each item l in $\mathcal{R}(i)$:
5: For each component m in $\{\mathbf{x}_{l*}\}$:
6: Compute $\beta(i, l, m)$ according to Eqns. (10) and (11)
7: Compute $\overline{\mathbf{x}}_l$ according to Eqn. (12)
8: Compute $\alpha(i, l)$ according to Eqns. (8) and (9)
9: $\mathbf{u}'_i \leftarrow \mathbf{u}_i + \sum_{l \in \mathcal{R}(i)} \alpha(i, l)\mathbf{p}_l$
10: $\hat{R}_{ijk} \leftarrow \mathbf{u}'_i \mathbf{v}_j - \mathbf{u}'_i \mathbf{v}_k$
11: For each parameter θ in $\{\mathbf{U}, \mathbf{V}, \mathbf{P}, \Theta\}$:
12: Update $\theta \leftarrow \theta + \eta \cdot (\frac{\exp^{-\hat{R}_{ijk}}}{1+\exp^{-\hat{R}_{ijk}}} \cdot \frac{\partial \hat{R}_{ijk}}{\partial \theta} + \lambda \cdot \theta)$.
13: **until** convergence
14: return **U**, **V**, **P** and Θ.

Item Attention

Algorithm

Input: User-item interaction matrix $\mathbf{R}$. Each item l is represented by a set of component features $\{x_{l*}\}$.

Output: Latent feature matrix $\mathbf{U}$, $\mathbf{V}$, $\mathbf{P}$ and parameters in attention model Θ

Initialize $\mathbf{U}$, $\mathbf{V}$ and $\mathbf{P}$ with Gaussian distribution. Initialize Θ with xavier [17].

repeat

    draw (i, j, k) from $\mathcal{R}_B$

    For each item l in $\mathcal{R}(i)$:

        For each component m in $\{\mathbf{x}_{l*}\}$:

            Compute $\beta(i, l, m)$ according to Eqns. (10) and (11)

        Compute $\overline{\mathbf{x}}_l$ according to Eqn. (12)

    Compute $\alpha(i, l)$ according to Eqns. (8) and (9)

    $\mathbf{u}'_i \leftarrow \mathbf{u}_i + \sum_{l \in \mathcal{R}(i)} \alpha(i, l)\mathbf{p}_l$

    $\hat{R}_{ijk} \leftarrow \mathbf{u}'_i \mathbf{v}_j - \mathbf{u}'_i \mathbf{v}_k$

    For each parameter θ in $\{\mathbf{U}, \mathbf{V}, \mathbf{P}, \Theta\}$:

        Update $\theta \leftarrow \theta + \eta \cdot \left(\frac{\exp^{-\hat{R}_{ijk}}}{1+\exp^{-\hat{R}_{ijk}}} \cdot \frac{\partial \hat{R}_{ijk}}{\partial \theta} + \lambda \cdot \theta\right)$.

until convergence

return $\mathbf{U}$, $\mathbf{V}$, $\mathbf{P}$ and Θ.

Compute scores and update model parameters

Hands On Code Slides

Hands On!

`models/acf.py`

@ `class ACF`

Model logic

```
class ACF(nn.Module):
    def __init__(self,
                 users,
                 items,
                 feature_path,
                 model_dim=128,
                 input_feature_dim=0,
                 tied_item_embedding=True,
                 device=None):

        super().__init__()
        self.pad_token = 0
        self.device = device

        # Should be moved to an ACFRecommender
        self.users = users
        self.items = items
        self.feature_path = feature_path
        self.model_dim = model_dim
        self.input_feature_dim = input_feature_dim

        self.all_items = torch.tensor(items)
        self.all_items = self.all_items + 1 if self.all_items.min() == 0 else self.all_items
        self.feature_data = self.load_feature_data(feature_path)
        num_items = max(self.all_items) + 1

        input_feature_dim = self.feature_data.shape[-1]
        self.item_model = nn.Embedding(num_items, self.model_dim, padding_idx=self.pad_token)
        self.user_model = ACFUserNet(users,
                                     items,
                                     emb_dim=self.model_dim,
                                     input_feature_dim=input_feature_dim,
                                     profile_embedding=self.item_model,
                                     device=self.device)
```

Hands On!

`models/acf.py`

@ `class ACF`

↓

Model logic

```
def forward(self, user_id, profile_ids, pos, neg, profile_mask):
    profile_features = self.get_features(profile_ids).to(self.device)

    user_output = self.user_model(user_id, profile_ids, profile_features, profile_mask)
    user = user_output['user']

    pos_pred = self.get_predictions(user, pos)
    neg_pred = self.get_predictions(user, neg)

    return pos_pred, neg_pred
```

```
def get_predictions(self, user, items):
    item_embeddings = self.item_model(items)
    prediction = self.score(user, item_embeddings)
    return prediction
```

```
def score(self, user, items):
    return (user * items).sum(1) / self.model_dim
```

Hands On!

`models/acf.py`

`@ class ACFUserNet`

↓

User level logic

```python
class ACFUserNet(nn.Module):
    """
    Get user embedding accounting to surpassed items
    """

    def __init__(self, users, items, emb_dim=128, input_feature_dim=0, profile_embedding=None, device=None):
        super().__init__()
        self.pad_token = 0

        self.emb_dim = emb_dim
        num_users = max(users) + 1
        num_items = max(items) + 1

        reduced_feature_dim = emb_dim
        self.feats = ACFFeatureNet(emb_dim, input_feature_dim, reduced_feature_dim) if input_feature_dim > 0 else None

        self.user_embedding = nn.Embedding(num_users, emb_dim)
        if not profile_embedding:
            self.profile_embedding = nn.Embedding(num_items, emb_dim, padding_idx=self.pad_token)
        else:
            self.profile_embedding = profile_embedding

        f = 1 if self.feats is not None else 0
        self.w_u = nn.Linear(emb_dim, emb_dim)
        self.w_v = nn.Linear(emb_dim, emb_dim)
        self.w_p = nn.Linear(emb_dim, emb_dim)
        self.w_x = nn.Linear(emb_dim, emb_dim)
        self.w = nn.Linear(emb_dim, 1)

        self._kaiming_(self.w_u)
        self._kaiming_(self.w_v)
        self._kaiming_(self.w_p)
        self._kaiming_(self.w_x)
        self._kaiming_(self.w)
```

Hands On!

`models/acf.py`

`@ class ACFUserNet`

↓

User level logic

```python
def forward(self, user_ids, profile_ids, features, profile_mask, return_component_attentions=False,
            return_profile_attentions=False, return_attentions=False):
    ...

    user = self.user_embedding(user_ids)

    profile = self.profile_embedding(profile_ids)

    features = features.flatten(start_dim=2, end_dim=3) # Add
    feat_output = self.feats(user, features, profile_mask, return_attentions=return_component_attentions)
    components = feat_output['pooled_features']

    user = self.w_u(user)
    profile_query = self.w_p(profile)
    components = self.w_x(components)

    profile_query = profile_query.permute((1,0,2))
    components = components.permute((1,0,2))

    alpha = F.relu(user + profile_query + components) # TODO: + item, Add curent_item emb (?)
    alpha = self.w(alpha)

    profile_mask = profile_mask.permute((1,0))
    profile_mask = profile_mask.unsqueeze(-1)
    alpha = alpha.masked_fill(torch.logical_not(profile_mask), float('-inf'))
    alpha = F.softmax(alpha, dim=0)

    alpha = alpha.permute((1,0,2))
    user_profile = (alpha * profile).sum(dim=1)

    user = user + user_profile
    output = {'user': user}
    if return_component_attentions:
        output['component_attentions'] = feat_output['attentions']
    if return_profile_attentions:
        output['profile_attentions'] = alpha.squeeze(-1)

    return output
```

Hands On!

models/acf.py

@ class ACFUserNet

```python
def forward(self, user_ids, profile_ids, features, profile_mask, return_component_attentions=False,
            return_profile_attentions=False, return_attentions=False):
    ...

    user = self.user_embedding(user_ids)

    profile = self.profile_embedding(profile_ids)

    features = features.flatten(start_dim=2, end_dim=3) # Add
    feat_output = self.feats(user, features, profile_mask, return_attentions=return_component_attentions)
    components = feat_output['pooled_features']

    user = self.w_u(user)
    profile_query = self.w_p(profile)
    components = self.w_x(components)

    profile_query = profile_query.permute((1,0,2))
    components = components.permute((1,0,2))

    alpha = F.relu(user + profile_query + components) # TODO: + item, Add curent_item emb (?)
    alpha = self.w(alpha)

    profile_mask = profile_mask.permute((1,0))
    profile_mask = profile_mask.unsqueeze(-1)
    alpha = alpha.masked_fill(torch.logical_not(profile_mask), float('-inf'))
    alpha = F.softmax(alpha, dim=0)

    alpha = alpha.permute((1,0,2))
    user_profile = (alpha * profile).sum(dim=1)

    user = user + user_profile
    output = {'user': user}
    if return_component_attentions:
        output['component_attentions'] = feat_output['attentions']
    if return_profile_attentions:
        output['profile_attentions'] = alpha.squeeze(-1)

    return output
```

User & profile latent factors

Hands On!

models/acf.py

@ class ACFUserNet

```
def forward(self, user_ids, profile_ids, features, profile_mask, return_component_attentions=False,
            return_profile_attentions=False, return_attentions=False):
    ...

    user = self.user_embedding(user_ids)

    profile = self.profile_embedding(profile_ids)

    features = features.flatten(start_dim=2, end_dim=3) # Add
    feat_output = self.feats(user, features, profile_mask, return_attentions=return_component_attentions)
    components = feat_output['pooled_features']

    user = self.w_u(user)
    profile_query = self.w_p(profile)
    components = self.w_x(components)

    profile_query = profile_query.permute((1,0,2))
    components = components.permute((1,0,2))

    alpha = F.relu(user + profile_query + components) # TODO: + item, Add curent_item emb (?)
    alpha = self.w(alpha)

    profile_mask = profile_mask.permute((1,0))
    profile_mask = profile_mask.unsqueeze(-1)
    alpha = alpha.masked_fill(torch.logical_not(profile_mask), float('-inf'))
    alpha = F.softmax(alpha, dim=0)

    alpha = alpha.permute((1,0,2))
    user_profile = (alpha * profile).sum(dim=1)

    user = user + user_profile
    output = {'user': user}
    if return_component_attentions:
        output['component_attentions'] = feat_output['attentions']
    if return_profile_attentions:
        output['profile_attentions'] = alpha.squeeze(-1)

    return output
```

Item represented as weighted components

Hands On!

models/acf.py

@ class ACFUserNet

Item-Level Attention

```python
def forward(self, user_ids, profile_ids, features, profile_mask, return_component_attentions=False,
            return_profile_attentions=False, return_attentions=False):
    ...

    user = self.user_embedding(user_ids)

    profile = self.profile_embedding(profile_ids)

    features = features.flatten(start_dim=2, end_dim=3) # Add
    feat_output = self.feats(user, features, profile_mask, return_attentions=return_component_attentions)
    components = feat_output['pooled_features']

    user = self.w_u(user)
    profile_query = self.w_p(profile)
    components = self.w_x(components)

    profile_query = profile_query.permute((1,0,2))
    components = components.permute((1,0,2))

    alpha = F.relu(user + profile_query + components) # TODO: + item, Add curent_item emb (?)
    alpha = self.w(alpha)

    profile_mask = profile_mask.permute((1,0))
    profile_mask = profile_mask.unsqueeze(-1)
    alpha = alpha.masked_fill(torch.logical_not(profile_mask), float('-inf'))
    alpha = F.softmax(alpha, dim=0)

    alpha = alpha.permute((1,0,2))
    user_profile = (alpha * profile).sum(dim=1)

    user = user + user_profile
    output = {'user': user}
    if return_component_attentions:
        output['component_attentions'] = feat_output['attentions']
    if return_profile_attentions:
        output['profile_attentions'] = alpha.squeeze(-1)

    return output
```

Hands On!

models/acf.py

@ class ACFUserNet

User representation formation

```
def forward(self, user_ids, profile_ids, features, profile_mask, return_component_attentions=False,
            return_profile_attentions=False, return_attentions=False):
    ...

    user = self.user_embedding(user_ids)

    profile = self.profile_embedding(profile_ids)

    features = features.flatten(start_dim=2, end_dim=3) # Add
    feat_output = self.feats(user, features, profile_mask, return_attentions=return_component_attentions)
    components = feat_output['pooled_features']

    user = self.w_u(user)
    profile_query = self.w_p(profile)
    components = self.w_x(components)

    profile_query = profile_query.permute((1,0,2))
    components = components.permute((1,0,2))

    alpha = F.relu(user + profile_query + components) # TODO: + item, Add curent_item emb (?)
    alpha = self.w(alpha)

    profile_mask = profile_mask.permute((1,0))
    profile_mask = profile_mask.unsqueeze(-1)
    alpha = alpha.masked_fill(torch.logical_not(profile_mask), float('-inf'))
    alpha = F.softmax(alpha, dim=0)

    alpha = alpha.permute((1,0,2))
    user_profile = (alpha * profile).sum(dim=1)

    user = user + user_profile
    output = {'user': user}
    if return_component_attentions:
        output['component_attentions'] = feat_output['attentions']
    if return_profile_attentions:
        output['profile_attentions'] = alpha.squeeze(-1)

    return output
```

Hands On!

`models/acf.py`

@ `class ACFFeatureNet`

Component level logic

```python
class ACFFeatureNet(nn.Module):
    """
    Process auxiliary item features into latent space.
    All items for user can be processed in batch.
    """
    def __init__(self, emb_dim, input_feature_dim, feature_dim, hidden_dim=None, output_dim=None):
        super().__init__()

        ...

        self.dim_reductor = nn.Linear(input_feature_dim, feature_dim)

        self.w_x = nn.Linear(feature_dim, hidden_dim)
        self.w_u = nn.Linear(emb_dim, hidden_dim)

        self.w = nn.Linear(hidden_dim, 1)

        self._kaiming_(self.w_x)
        self._kaiming_(self.w_u)
        self._kaiming_(self.w)
```

Hands On!

`models/acf.py`

@ `class ACFFeatureNet`

↓

Component level logic

```python
def forward(self, user, components, profile_mask, return_attentions=False):
    x = self.dim_reductor(components) # Add
    x = x.movedim(0, -2) # BxPxHxD => PxHxBxD

    x_tilde = self.w_x(x)
    user = self.w_u(user)

    beta = F.relu(x_tilde + user)
    beta = self.w(beta)

    beta = F.softmax(beta, dim=1)

    x = (beta * x).sum(dim=1)
    x = x.movedim(-2, 0) # PxBxD => BxPxD

    feature_dim = x.shape[-1]
    profile_mask = profile_mask.float()
    profile_mask = profile_mask.unsqueeze(-1).expand((*profile_mask.shape, feature_dim))

    x = profile_mask * x
    output = {'pooled_features': x}
    if return_attentions:
        output['attentions'] = beta.squeeze(-1).squeeze(-1)
    return output
```

Hands On!

models/acf.py

@ class ACFFeatureNet

Dimensionality reduction

```python
def forward(self, user, components, profile_mask, return_attentions=False):
    x = self.dim_reductor(components) # Add
    x = x.movedim(0, -2) # BxPxnxD => PxnxBxD

    x_tilde = self.w_x(x)
    user = self.w_u(user)

    beta = F.relu(x_tilde + user)
    beta = self.w(beta)

    beta = F.softmax(beta, dim=1)

    x = (beta * x).sum(dim=1)
    x = x.movedim(-2, 0) # PxBxD => BxPxD

    feature_dim = x.shape[-1]
    profile_mask = profile_mask.float()
    profile_mask = profile_mask.unsqueeze(-1).expand((*profile_mask.shape, feature_dim))

    x = profile_mask * x
    output = {'pooled_features': x}
    if return_attentions:
        output['attentions'] = beta.squeeze(-1).squeeze(-1)
    return output
```

Hands On!

models/acf.py

@ class ACFFeatureNet

Component-Level Attention

```python
def forward(self, user, components, profile_mask, return_attentions=False):
    x = self.dim_reductor(components) # Add
    x = x.movedim(0, -2) # BxPxHxD => PxHxBxD

    x_tilde = self.w_x(x)
    user = self.w_u(user)

    beta = F.relu(x_tilde + user)
    beta = self.w(beta)

    beta = F.softmax(beta, dim=1)

    x = (beta * x).sum(dim=1)
    x = x.movedim(-2, 0) # PxBxD => BxPxD

    feature_dim = x.shape[-1]
    profile_mask = profile_mask.float()
    profile_mask = profile_mask.unsqueeze(-1).expand((*profile_mask.shape, feature_dim))

    x = profile_mask * x
    output = {'pooled_features': x}
    if return_attentions:
        output['attentions'] = beta.squeeze(-1).squeeze(-1)
    return output
```

Hands On!

`trainers/acf_trainer.py`

@ `class ACFTrainer`

↓

Training logic

```python
class ACFTrainer():
    """
    Handles training process
    """
    def __init__(self, model, datasets, loss, optimizer, version, batch_size=100, device=None,
                 max_profile_size=9, checkpoint_dir=None):
        """
        Parameters
        ----------
        model: initialized UserNet
        dataset: initialized MovieLens
        loss: one of the warp functions
        optimizer: torch.optim
        run_name: directory to save results
        batch_size: number of samples to process for one update
        device: gpu or cpu
        """
        self.pad_token = 0

        self.version = version
        self.epoch = 0
        self.best_loss = np.inf
        self.loss = loss
        self.optimizer = optimizer
        self.batch_size = batch_size

        self.device = get_device(device)
        self.model = model
        self.model = self.model.to(self.device)

        self.train, self.test = datasets
        self.all_items = self.preprocess_inputs(self.train.items, to_tensor=True)

        self.train_loader = DataLoader(self.train, batch_size=batch_size, shuffle=True,
                                       collate_fn=generate_collate_fn(max_profile_size), num_workers=8)
        self.test_loader = DataLoader(self.test, batch_size=batch_size, shuffle=True,
                                      collate_fn=generate_collate_fn(max_profile_size), num_workers=1)
```

Hands On!

`trainers/acf_trainer.py`

@ `class ACFTrainer`

Training logic

```
def fit(self, num_epochs, k=10):
    num_train_batches = len(self.train) / self.batch_size
    num_test_batches = len(self.test) / self.batch_size
    for epoch in tqdm(range(num_epochs)):
        self.epoch = epoch
        for phase in ['train', 'val']:
            self.logger.epoch(epoch, phase)
            self.model.train(phase == 'train')
            loss = 0
            cur_step = 0
            if phase == 'train':
                t = tqdm(self.train_loader)
                for batch in t:
                    self.optimizer.zero_grad()
                    cur_loss  = self.training_step(batch)
                    self.optimizer.step()
                    loss += cur_loss
                    cur_step += 1
                    avg_loss = loss / cur_step

                    t.set_description(f"Average Loss {avg_loss:.4f}")
                    t.refresh()

                loss /= num_train_batches
                self.logger.metrics(loss, 0, epoch, phase)
            else:
                with torch.no_grad():
                    for batch in tqdm(self.test_loader):
                        cur_loss = self.validation_step(batch)
                        loss += cur_loss
                    loss /= num_test_batches
                    # self.logger.metrics(loss, self.score(k=k), epoch, phase)
                    self.logger.metrics(loss, 0.0, epoch, phase)

                    if loss < self.best_loss:
                        self.best_loss = loss
                        self.logger.save(self.state, epoch)
```

Hands On!

`trainers/acf_trainer.py`

`@ class ACFTrainer`

`trainers/loss.py`

Weston, J., Bengio, S., & Usunier, N. (2011). Wsabie: Scaling up to large vocabulary image annotation.

```python
def training_step(self, batch):
    user_id, profile_ids, pos, neg = self.preprocess_inputs(*batch)
    profile_mask = self.get_profile_mask(profile_ids)
    pos_pred, neg_pred = self.model(user_id, profile_ids, pos, neg, profile_mask)

    loss = self.loss(pos_pred, neg_pred)
    loss.backward()
    return loss.item()
```

```python
def bpr_loss(pos, neg, b=0.0, collapse=True):
    res = torch.sigmoid(neg - pos + b)
    if collapse:
        res = res.mean()
    return res


def warp_loss(pos, neg, b=1, collapse=True):
    loss = bpr_loss(pos, neg, b, collapse=False)
    m = (loss > 0.5).float()
    m *= torch.log(m.sum() + 1) + 1
    res = m * loss
    if collapse:
        res = res.mean()
    return res
```