Making Neural Networks Interpretable with Attribution: Application to Implicit Signals Prediction

Recsys '20

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Deezer Research

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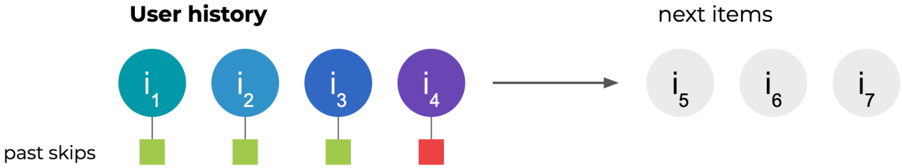
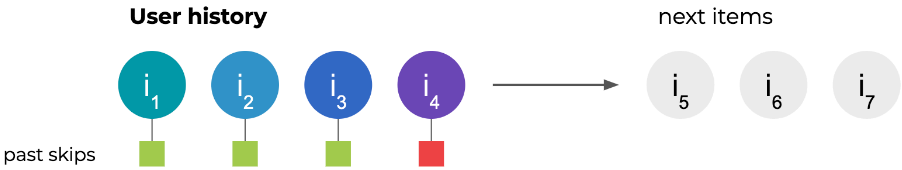
Interpretation for Recommender Systems

- Explain recommended items [4, 9, 11]
- Inspect recommender system models
  - *model performances, fairness, ...*
  - Interpret **implicit data** [5]
    interaction, skips, user churn, ...

e.g. listening session



e.g. listening session



What will be predicted as a skip?

- a user disliking a music? *musical features*
- a user exploring the music catalog? *interaction features*
- something else?

Attribution

Supervised task: *r.v.* $X \in \mathbb{R}^n$, $Y \in \{0, 1\}$

$$X \xrightarrow{f_\theta} Y$$

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Attribution: *r.v.* $S \subset [n]$ be a random set of indices

- *completeness:*

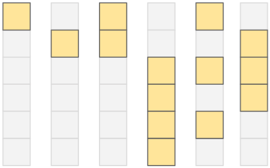
$$X_{|S} \xrightarrow{f_{\theta|S}} Y$$

- *interpretability:* $\mathbb{E}[\mathrm{Card}(S)]$ is as small as possible

Another way to see attribution

With infinite computing capacities,

1. 2^n possibilities for $S: s_1, \dots s_{2^n}$;
2. Train all restricted models $f_1, \dots f_{2^n}$;
3. Select model k^* with **small domain** and **low error**.



$\rightarrow$ *NP-hard, overlapping subsets, ...*

... for real applications

In real-data applications,

- *gradient-based* proxy [1, 8, 10] or *approximations* [7, 2] ;
- *intrinsically attributable* models

$$e.g.\ f(x) = \sum_{i=1}^{n} f_i(x_i)\ [3]$$

$$e.g.\ f(x) = \sum_{i=1}^{n} f_i(x_i) + \sum_{i<j} \tilde{f}_{i,j}(x_i, x_j)\ [6]$$

Our method: $\boxed{f(x) = \sum_{s\in\mathcal{S}} \alpha_s(x_{|s}) f_s(x_{|s})}$

Contributions

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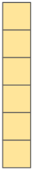
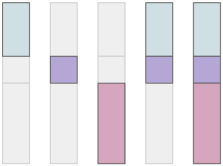
2. we derive a fast algorithm to train our networks ;
3. we demonstrate the effectiveness of our method for **prediction** and **interpretation** on synthetic and real-data tasks (*e.g. sequential skip prediction*).

Mask space reduction



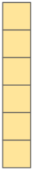
X

→ Reduce the 2^n possible values for S.



Considered candidates

Mask space reduction



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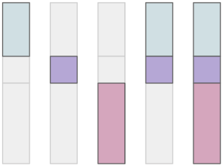


Considered candidates

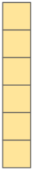
<u>Group-sparsity</u>: we partition $[n]$

$$\mathcal{X} = \{X_1, \ldots X_N\}$$

Codomain of S now has a size

$$2^N \ll 2^n$$

Mask space reduction



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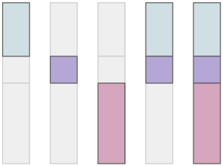

Considered candidates

Group-sparsity: we partition $[n]$

$$\mathcal{X} = \{X_1, \dots X_N\}$$

Codomain of S now has a size

$$2^N \ll 2^n$$

Structured sparsity: we restrict solutions to follow defined patterns

$$\mathcal{S} \subset \mathcal{P}(\mathcal{X})$$

Codomain of S now has a size

$$H = |\mathcal{S}| < 2^N \ll 2^n$$

Mixture of experts

$f^1, \ldots f^H$ are **restricted** expert models

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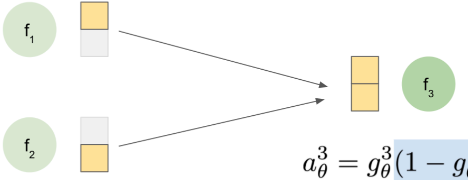
$$f_\theta(x) = \frac{\sum_{s \in \mathcal{S}} \alpha_\theta^s(x_{|s}) f_\theta^s(x_{|s})}{\sum_{s \in \mathcal{S}} \alpha_\theta^s(x_{|s})} \tag{1}$$

Boosting

Example: $X \in \mathbb{R}^2$, S is $\{1\}$, $\{2\}$ or $\{1, 2\}$:

$$a_\theta^1 = g_\theta^1$$

$$a_\theta^2 = g_\theta^2$$



$$a_\theta^3 = g_\theta^3 (1 - g_\theta^1)(1 - g_\theta^2)$$

Residuality

Boosting

Example: $X \in \mathbb{R}^2$, S is $\{1\}$, $\{2\}$ or $\{1,2\}$:

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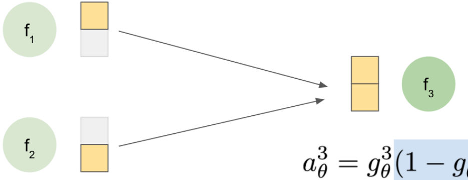


$a_\theta^3 = g_\theta^3(1 - g_\theta^1)(1 - g_\theta^2)$

Residuality

General case: $\mathrm{child}(s) = \{t | t \subsetneq s\}$

$$\boxed{\alpha_\theta^s(x) = g_\theta^s(x_{|s}) \prod_{t \in \mathrm{child}(s)} (1 - g_\theta^t(x_{|t}))} \quad (2)$$

with $g_\theta^s : x_{|s} \mapsto [0,1]$

Selection modelisation

Using a deep neural network $F^s_\theta : x_{|s} \mapsto [-1, 1]$:

Predictions: binary setting

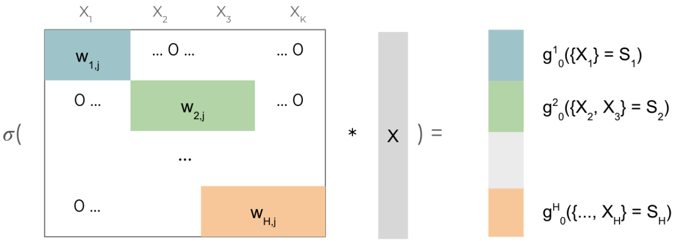
$$f^s_\theta(x) = (F^s_\theta(x) + 1)/2$$

Selections:

$$g^s_\theta(x) = |F^s_\theta(x)|$$

Generalisation

- Can be combined in a single neural network ;
  spoiler: *by masking the weight matrices*



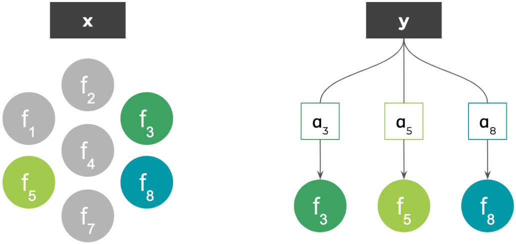
- Time dimension added ;
- RNN, **Transformer**, ... can be easily made interpretable.

The section is fully detailed in the paper!

See also: `github.com/deezer/interpretable_nn_attribution`

Training

- Naive approach: train sequentially with residuals
- Instead → *Generalised Expectation-Maximisation*



Submodel selection

Gradient-step

Results - completeness

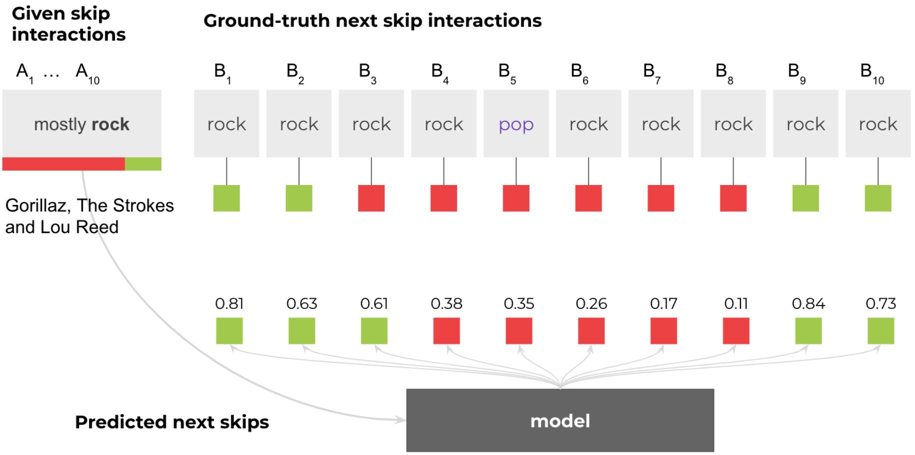
Model	Acc (%)	Acc@1 (%)	MAA (%)
Baseline	70.1	73.3	60.9
Transformer	78.9 ± 0.1	83.4 ± 0.1	70.2 ± 0.1
Interpretable Transformer	77.7 ± 0.1	82.4 ± 0.1	68.8 ± 0.1

Table: Deezer sequential skip prediction test results

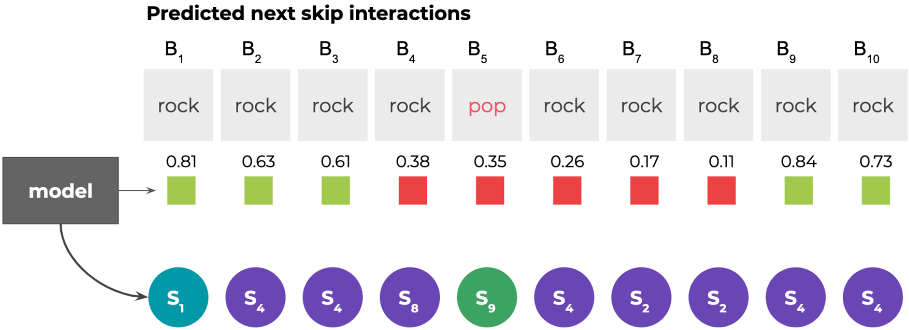
Model	Acc (%)	Acc@1 (%)	MAA (%)
Baseline	63.0	74.2	54.3
Transformer	72.2 ± 0.2	80.0 ± 0.2	62.8 ± 0.2
Interpretable Transformer	70.9 ± 0.2	78.8 ± 0.2	61.1 ± 0.2

Table: Spotify sequential skip prediction test results

Results - interpretation I



Results - interpretation II



Persistence	**0.89**	0.14	0.01	0	0	0	0	0	0	0
Interaction	0.07	**0.73**	**0.92**	**0.53**	0.47	**0.70**	**0.68**	**0.67**	**0.69**	**0.63**
Musical	0.04	0.13	0.06	0.30	**0.52**	0.30	0.32	0.32	0.30	0.35

Thank you!

Repository: github.com/deezer/interpretable_nn_attribution

Future directions:

- Learnable space of candidates $\mathcal{S}$
- Attribution solutions geometry

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