# Algorithmes de recommandations Netflix

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# Sommaire

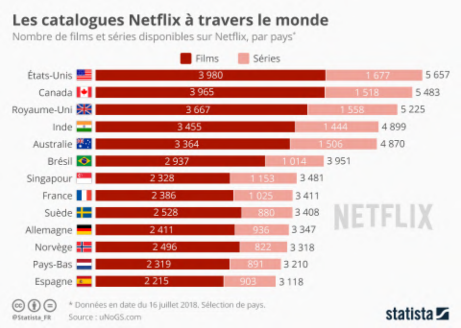
- Introduction
- L'algorithme de recommandation basé sur la factorisation matricielle
- Les défis liés
- Les impacts
- Conclusion
- Bibliographie

# Sommaire

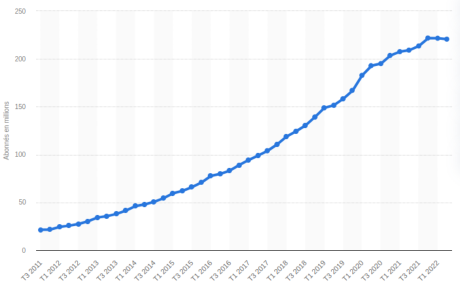
# Introduction

## What's Netflix?

- Entreprise américaine
- Fondée en 1997 par Reed Hastings et Marc Randolph
- Plateforme de streaming et de vidéos à la demande
- Implanté dans 190 pays




(a) Nombre de titres selon le plays




(b) Évolution du nombre d'abonnés

# Introduction

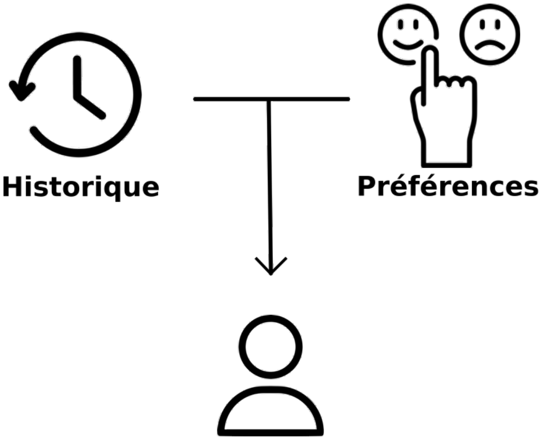



Figure: Version simplifiée de l'algorithme de recommandation de Netflix

# Sommaire

- Introduction
- **L'algorithme de recommandation basé sur la factorisation matricielle**

# Partie I : L'algorithme de recommandation basé sur la factorisation matricielle

- Faisant partie du filtrage collaboratif...
- Ce dont on dispose :

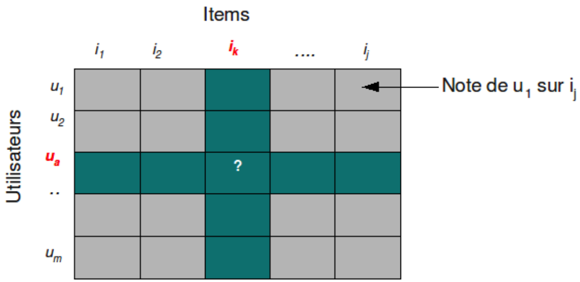



Figure: Matrice utilisateur-item notée $\mathcal{R}$

# Partie I : L'algorithme de recommandation basé sur la factorisation matricielle

**Problème !!**

# Partie I : L'algorithme de recommandation basé sur la factorisation matricielle

**Solution : Factorisation Matricielle**

# Partie I : L'algorithme de recommandation basé sur la factorisation matricielle

On note :

- $\mathcal{R} \in \mathcal{M}_{n,p}(\mathbb{R})$,
- $\mathcal{P} \in \mathcal{M}_{n,k}(\mathbb{R})$,
- $\mathcal{Q} \in \mathcal{M}_{k,p}(\mathbb{R})$.

**L'objectif est de trouver P et Q tels que R = PQ.**

# Partie I : L'algorithme de recommandation basé sur la factorisation matricielle

La fonction objective :

$$\min_{q,p} \sum_{(u,i)\in\kappa} \left(r_{ui} - q_i^T p_u\right)^2 + \lambda \left(\|q_i\|^2 + \|p_u\|^2\right)$$

où, $\kappa$ est l'ensemble des paires $(u, i)$ pour lesquels $r_{ui}$ est connue (training set).

## Partie I : L'algorithme de recommandation basé sur la factorisation matricielle

La méthode de descente de gradient stochastique (DGS) se fait avec :

$$\begin{aligned} q_i &\leftarrow q_i + \gamma \cdot (e_{ui} \cdot p_u - \lambda \cdot q_i) \\ p_u &\leftarrow p_u + \gamma \cdot (e_{ui} \cdot q_i - \lambda \cdot p_u) \end{aligned}$$

où $e_{ui} \stackrel{\text{def}}{=} r_{ui} - q_i^T p_u$ est l'erreur de prédiction pour l'élément $r_{ui}$ de la matrice de notation.

**Les avantages et les limites de la méthode de descente de gradient stochastique (DGS)**

# Partie I : L'algorithme de recommandation basé sur la factorisation matricielle

Une alternative : **La méthode des moindres carrés alternés (MCA)**

**Les avantages et les limites de la méthode des moindres carrés alternés (MCA)**

**Les avantages et les limites de la factorisation matricielle**

# Sommaire

## Le problème de démarrage à froid (The Cold Start Problem)

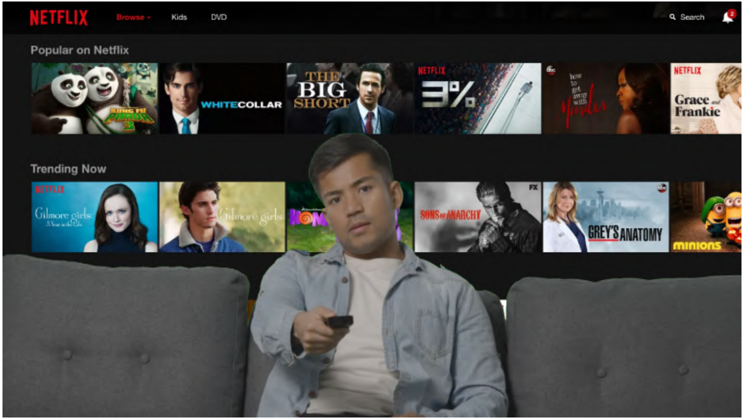



Figure: Chercher un titre à visionner sur Netflix

$$\begin{pmatrix} 5 & 4 & 5 & 1 & 0 \\ 5 & 0 & 3 & 5 & 1 \\ ? & ? & ? & ? & ? \\ 2 & 1 & 3 & 4 & 4 \\ 1 & 0 & 1 & 2 & 1 \end{pmatrix}$$

# Partie II: Les défis liés aux systèmes de recommandations

## Le problème de démarrage à froid (The Cold Start Problem)

Figure: Jump start

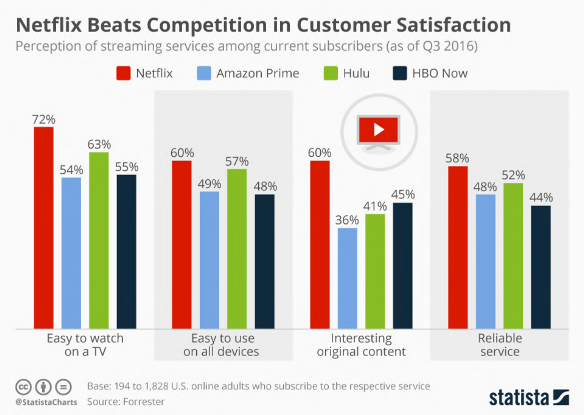
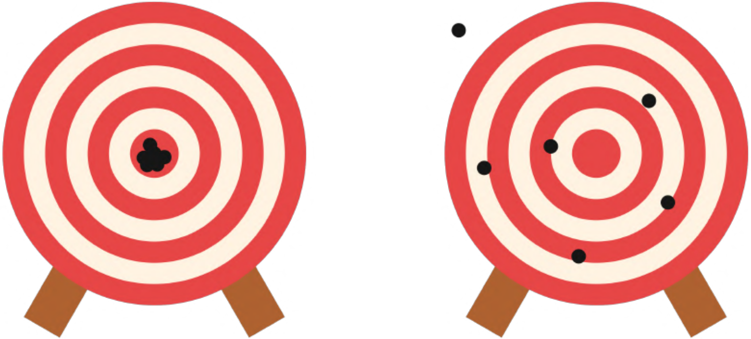



Figure: Satisfaction des utilisateurs Netflix

## Les biais liés aux systèmes de recommandations



(a) Attente (b) Réalité

Table 1. The characteristics of seven types of biases in recommendation and the bias amplification in loop.

| Types | Stages in Loop | Cause | Effect | Major solutions |
|---|---|---|---|---|
| Selection Bias | User→Data | Users' self-selection | Skewed observed rating distribution | Data Imputation; Propensity Score; Joint Generative Model; Doubly Robust Model |
| Exposure Bias | User→Data | Item Popularity; Intervened by systems; User behavior and background | Unobserved interactions do not mean negative | Giving confidence weights by heuristic, sampling or exposure-based model; Propensity Score; Causality-based Model |
| Conformity Bias | User→Data | Conformity | Skewed interaction labels | Modeling social or popularity effect |
| Position Bias | User→Data | Trust top of lists; Exposed to top of lists | Unreliable positive data | Click models; Propensity Score; Trust-aware Model |
| Inductive Bias | Data→Model | Added by researchers or engineers | Better generalization, lower variance or Faster recommendation | - |
| Popularity Bias | Model→User | Algorithm and unbalanced data | Matthew effect | Regularization; Adversarial Learning; Causal Graph |
| Unfairness | Model→User | Algorithm and unbalanced data | Unfairness for some groups | Rebalancing; Regularization; Adversarial Learning; Causal Modeling |
| Bias amplification in Loop | All | Feedback loop | Enhance and spread bias | Break the loop by collecting random data or using reinforcement learning |

(c) Différents types de biais

# Partie II: Les défis liés aux systèmes de recommandations

## Les biais liés aux systèmes de recommandations

Table 2. A lookup table for the reviewed methods for recommendation debiasing.

| Addressed issues | Categories | | How? | Strengths? | Weaknesses? | Publications |
|---|---|---|---|---|---|---|
| Selection Bias | Evaluator | Propensity Score | Weight the data | General, Theoretical-soundness | Requiring proper propensities | [143] |
| | | ATOP | Specific design | Theoretical-soundness | Requiring two strong assumptions | [149] |
| | Training | Joint Generative Model | Model missing mechanism | Explainable | Requiring assumptions on data generation, Hard to train | [30, 66, 87, 115, 116, 178] [189] |
| | | Data Imputation | Impute pseudo-labels | Simple | Highly sensitive to pesduo-labels | [140, 149, 150] |
| | | Propensity Score | Weight the data | Theoretical-soundness | High variance, Requiring proper propensities | [143, 177] |
| | | Doubly Robust Model | Impute+Weight | Theoretical-soundness, Robust | Requiring proper propensities or pesduo-labels | [176] |
| Conformity Bias | Modeling popularity influence | | Disentangle conformity effect from user preference | Explainable | Requiring assumptions on data generation | [110, 215, 217] |
| | Modeling social influence | | Disentangle social effect from user preference | Explainable | Requiring assumptions on data generation | [24, 112, 155, 172] |
| Exposure Bias | Evaluator | Propensity Score | Weight the data | Theoretical-soundness | Requiring proper propensities | [190] |
| | Training | Heuristic | Down-weight unobserved data heurstically | Simple | Coarse-grained, Heuristical | [45, 65, 68, 128, 129, 194] [100, 141] |
| | | Sampling | Down-weight unobserved data via sampling | Efficient | Coarse-grained, Requiring heuristic or side information | [32, 46, 47, 138, 175, 194] |
| | | Exposure-based model | Weight the data via exposure model | Explainable, Learn flexible weights | Hard to train | [29, 31, 32, 102, 163] |
| | | Propensity Scores | Weight the observed data | Theoretical-soundness | Requiring proper propensities, High variance | [141, 219] |
| | | Causality-based Methods | Remove spurious associations via causal inference | Explainable | Requiring assumptions on data generation | [108, 187, 191, 208] |
| | | Others | - | - | - | [113, 125, 126, 169, 204] [12, 42, 142, 181] |

(d) Différentes méthodes pour débiaiser selon les types de biais

# Partie II: Les défis liés aux systèmes de recommandations

## Les biais liés aux systèmes de recommandations

| | | | | | |
|---|---|---|---|---|---|
| Position Bias | Click Models | Model the generative process of clicks | Explainable | Requiring assumptions on data generation, hard to train | [26, 41, 48, 59, 103, 205] [74, 224] |
| | Propensity Score | Weight the data | Theoretical-soundness | High variance, Requiring proper propensities, Fail to model trust | [6, 67, 77, 136, 144, 153, 169] [10, 52, 77, 77, 134, 157, 171] [8, 35, 60] |
| | Trust-aware Models | Introduce offset terms to remove trust effect | Theoretical-soundness, Capture trust effect | High variance, Requiring proper propensities, Fail to model trust | [7, 158] |
| For multiple data biases and their combinations | Universal model | Transfer the knowledge from unbiased data to perform debiasing | Universal, Adaptive | Requiring a set of unbiased data | [17, 28, 106, 107] |
| Popularity Bias | Regularization | Introduce regularization terms | Simple, Straightforward | Possibly hurt accuracy | [2, 38, 83, 179, 221] |
| | Adversarial Learning | Leverage adversary to bridge the gap between niche and popular items | Balancing representation | Possibly hurt accuracy | [91] |
| | Causal Graph | Leverage causal graph to elucidate and mitigate popularity bias | Explainable | Requiring assumptions on data generation | [167, 180, 208, 215, 217] |
| | Others | - | - | - | [1, 19] |
| Unfairness | Rebalancing | Directly balance the data or recommendation results | Straightforward | Possibly hurt accuracy | [11, 15, 57, 57, 98, 133, 199] [22, 53, 135, 146] |
| | Regularization | Formulate the fairness criteria as a regularizer | Straightforward | Possibly hurt accuracy | [80–82, 84, 147, 188, 200] [2, 14, 21, 105, 192, 193] |
| | Adversarial Learning | Leverage adversary to isolate the effect of sensitive attributes | Fair representation | Possibly hurt accuracy | [13, 18, 50, 99, 183] |
| | Causal Modeling | Estimate fairness with intervening sensitive attributes | Explainable, Counterfactual fairness | Requiring assumptions on data generation | [93, 93, 122, 185, 186, 202] |
| | Others | - | - | - | [55, 69, 97] |
| Loop effect | Uniform Data | Intervene in the system with a random logging policy | Straightforward, Effective | Hurting the user experience and the system profit | [17, 73, 107, 107, 139, 196] [28, 195] |
| | Reinforcement learning | Intervene in the system with a smarter strategy for long-term benefits | Adaptively balancing exploration-exploitation | Hard to train, Off-policy evaluation is chanllenging | [36, 96, 161, 173, 209, 213, 214] [27, 34, 70, 170, 210–212, 216] [70, 72, 117, 154] |
| | Others | - | - | - | [148, 152] |

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(e) Différentes méthodes pour débiaiser selon les types de biais

# Partie II: Les défis liés aux systèmes de recommandations

## Les biais liés aux systèmes de recommandations

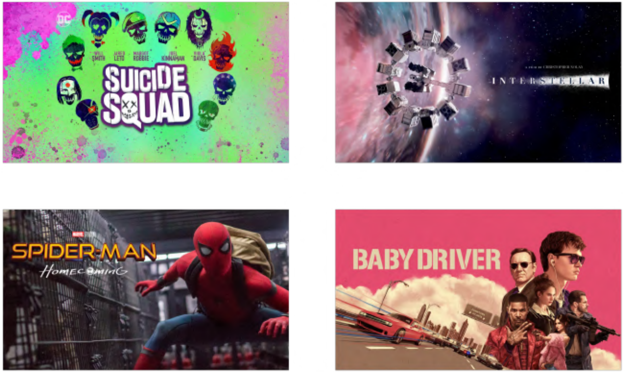



Figure: Biais d'exposition

$$R(\hat{Z}) = \frac{1}{|\mathcal{U}|} \sum_{u \in \mathcal{U}} \frac{1}{|\mathcal{S}_u|} \sum_{i \in \mathcal{G}_u} c\left(\hat{Z}_{ui}\right)$$

Figure: Correction du biais d'exposition par IPS

$$\begin{aligned}
\text{AUC} &: c\left(\hat{Z}_{ui}\right) = 1 - \frac{\hat{Z}_{u,i}}{|\mathcal{I}|} \\
\text{DCG} &: c\left(\hat{Z}_{ui}\right) = \frac{1}{\log_2\left(\hat{Z}_{ui} + 1\right)} \\
\text{DCG@k} &: c\left(\hat{Z}_{ui}\right) = \frac{1\left\{\hat{Z}_{ui} \leq k\right\}}{\log_2\left(\hat{Z}_{ui} + 1\right)} \\
\text{Recall@k} &: c\left(\hat{Z}_{ui}\right) = 1\left\{\hat{Z}_{ui} \leq k\right\}
\end{aligned}$$

Figure: Différents types de métriques

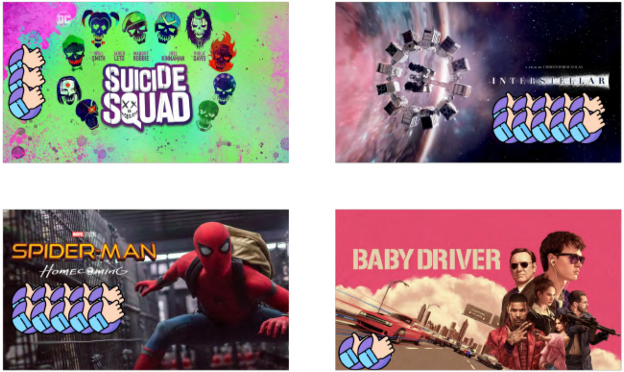



Figure: Biais de sélection

$$\hat{H}_{IPS}(\hat{r} \mid \rho) = \frac{1}{|\mathcal{U}||\mathcal{I}|} \sum_{(u,i):s_{ui}=1} \frac{\delta\left(\hat{r}_{ui}, r_{ui}\right)}{\rho_{ui}}$$

Figure: Correction du biais de sélection par IPS

# Partie II: Les défis liés aux systèmes de recommandations

## Les biais liés aux systèmes de recommandations

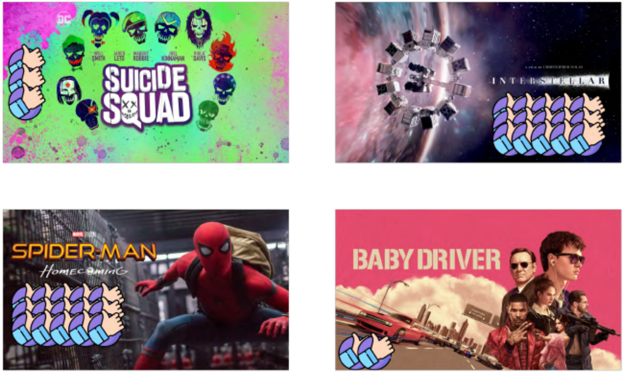



Figure: Biais de popularité

$$\min_{\boldsymbol{\Theta}} \mathcal{L}_{\text{Rec}} + \gamma PCC\left(\widehat{\mathbf{R}}_{+}, pop(\mathcal{I})\right)^2$$

Figure: Correction du biais de popularité par régularisation avec coefficient de corrélation de Pearson

# Partie II: Les défis liés aux systèmes de recommandations

## Les biais liés aux systèmes de recommandations

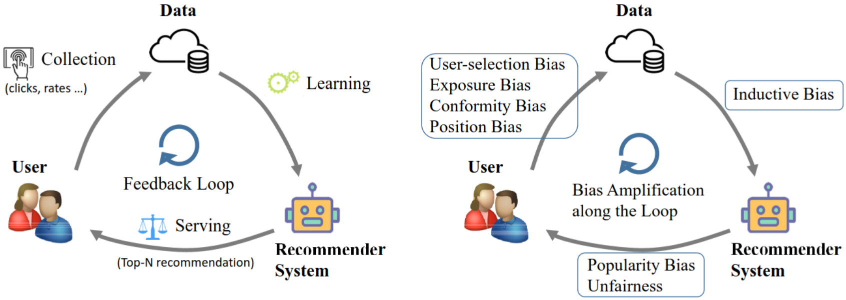


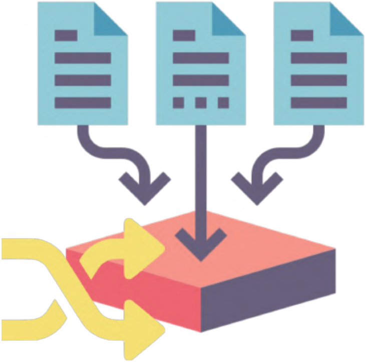

Fig. 2. Feedback loop in recommendation, where biases occur in different stages.

(a) "Feedback Loop"

# Partie II: Les défis liés aux systèmes de recommandations
## Les biais liés aux systèmes de recommandations


# Partie II: Les défis liés aux systèmes de recommandations

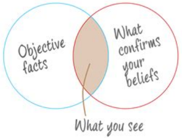
## Les biais liés aux systèmes de recommandations

# Sommaire

- Introduction
- L'algorithme de recommandation basé sur la factorisation matricielle
- Les défis liés
- **Les impacts**

(e) Personne n'est connecté à tout le monde




(f) Ce que l'on aime ne reflète pas ce que la majorité aime

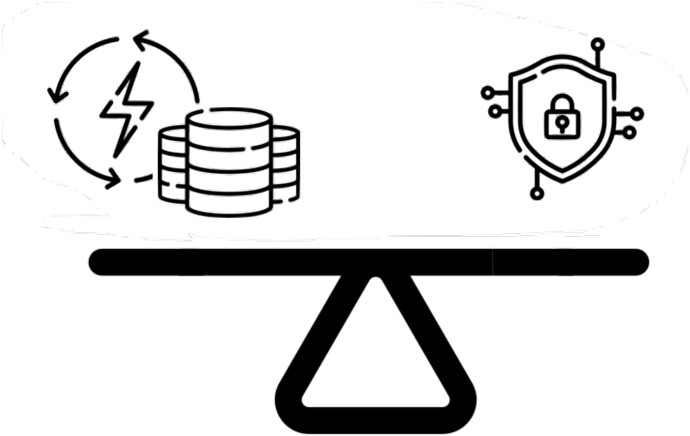


Figure: Choisir entre une expérience accrue et le respect de la protection des données

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# Bibliographie


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- Netflix Beats Competition in Customer Satisfaction
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