IIC3666 - Sistemas Recomendadores

# Widespread Flaws in Offline Evaluation of Recommender Systems

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# Contexto

Contexto

# A/B Testing

- Aproximacion limitada, debido a KPIs
- Division de trafico
- Leak de información
- Sesgos
- Costos y lentitud
- Falta de reproducibilidad

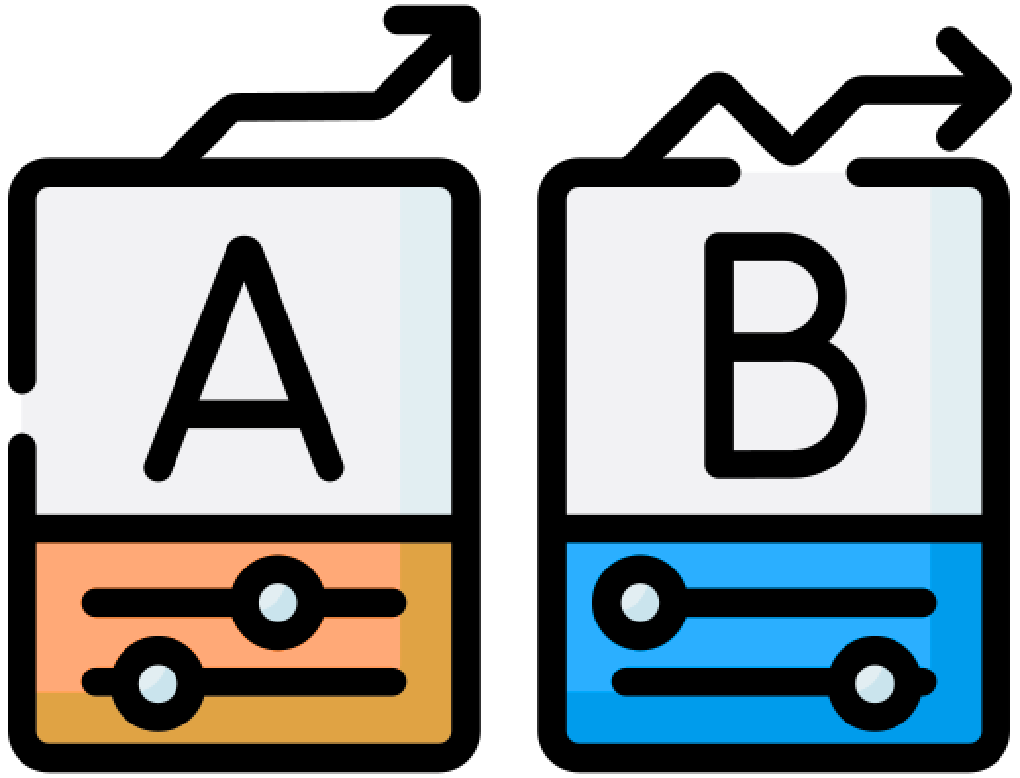



image: Flaticon.com

**A/B Testing**

# Evaluacion Offline

## 4 errores

- Dataset-task Mismatch
- Overzealous preprocessing
- Information leaking through time
- Negative sampling during testing

# Testing

- Next item prediction
- Session-based Recomender
- Behaviour prediction (eventos + interacciones con recomendador)
- recall@N y MRR@N
- GRU4Rec

# Datasets

**No Secuenciales (Rating):**

- Amazon (beauty)
- Movie Lens
- Steam
- Yelp

**Secuenciales:**

- Rees46
- Coveo (artificial)
- Retail Rocket

# Dataset-Task Mismatch

Dataset-Task Mismatch

# Ejemplos de errores

- Rating como feedback implicito
- Recomendación secuencial erronea
- Colisiones de eventos en secuencias

Dataset-Task Mismatch

# Datasets

Table 1. Basic statistics of train/test splits and event collision rate of the datasets

| Dataset | Training set #Events | Training set #Sequences | Training set #Days | Test set #Events | Test set #Sequences | Test set #Days | #Items | Event time collisions Proportion | Event time collisions Event% |
|---|---|---|---|---|---|---|---|---|---|
| Amazon (Beauty) | 724,440 | 215,595 | 4,907 | 30,191 | 11,452 | 56 | 38,606 | 31.89% | 33.03% |
| MovieLens10M | 9,861,612 | 69,141 | 5,054 | 99,022 | 737 | 56 | 10,066 | 17.83% | 27.33% |
| Steam | 4,856,479 | 900,878 | 2,582 | 46,039 | 16,916 | 56 | 12,229 | 7.67% | 13.49% |
| Yelp | 5,583,947 | 810,015 | 6,091 | 15,437 | 5,183 | 91 | 132,895 | 0.05% | 0.06% |
| Rees46 | 67,575,203 | 10,190,006 | 60 | 1,054,210 | 166,841 | 1 | 172,756 | 0.03% | 0.04% |
| Coveo | 1,411,113 | 165,673 | 17 | 52,501 | 7,748 | 1 | 10,868 | 0.00% | 0.00% |
| RetailRocket | 750,832 | 196,234 | 131 | 29,148 | 8,036 | 7 | 36,824 | 0.05% | 0.05% |

Dataset-Task Mismatch

# Resultados

- GRU v/s Feed Forward

Table 2. Recommendation accuracy using the same model with and without sequence modelling

| Dataset | Model w/ sequence modelling | | | | Model w/o sequence modelling | | | | Relative change | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Recall@N | | MRR@N | | Recall@N | | MRR@N | | Recall@N | | MRR@N | |
| | N=5 | N=20 | N=5 | N=20 | N=5 | N=20 | N=5 | N=20 | N=5 | N=20 | N=5 | N=20 |
| Rees46 | 0.3010 | 0.5293 | 0.1778 | 0.2008 | 0.2594 | 0.4785 | 0.1474 | 0.1694 | -13.80% | -9.58% | -17.09% | -15.67% |
| Coveo | 0.1496 | 0.3135 | 0.0852 | 0.1010 | 0.1289 | 0.2678 | 0.0734 | 0.0868 | -13.83% | -14.59% | -13.85% | -14.05% |
| Retailrocket | 0.3237 | 0.5186 | 0.1977 | 0.2175 | 0.2747 | 0.4652 | 0.1613 | 0.1806 | -15.13% | -10.30% | -18.42% | -16.97% |
| Amazon (Beauty) | 0.0784 | 0.1319 | 0.0527 | 0.0579 | 0.0779 | 0.1271 | 0.0531 | 0.0579 | -0.71% | -3.61% | 0.86% | 0.00% |
| MovieLens10M | 0.1728 | 0.3264 | 0.1062 | 0.1211 | 0.1276 | 0.2440 | 0.0763 | 0.0875 | -26.18% | -25.23% | -28.16% | -27.68% |
| Steam | 0.1117 | 0.2371 | 0.0662 | 0.0781 | 0.1035 | 0.2208 | 0.0622 | 0.0735 | -7.38% | -6.87% | -5.99% | -5.96% |
| Yelp | 0.0702 | 0.1627 | 0.0371 | 0.0457 | 0.0657 | 0.1625 | 0.0353 | 0.0445 | -6.46% | -0.12% | -4.78% | -2.51% |

# Overzealous preprocessing

Overzealous preprocessing

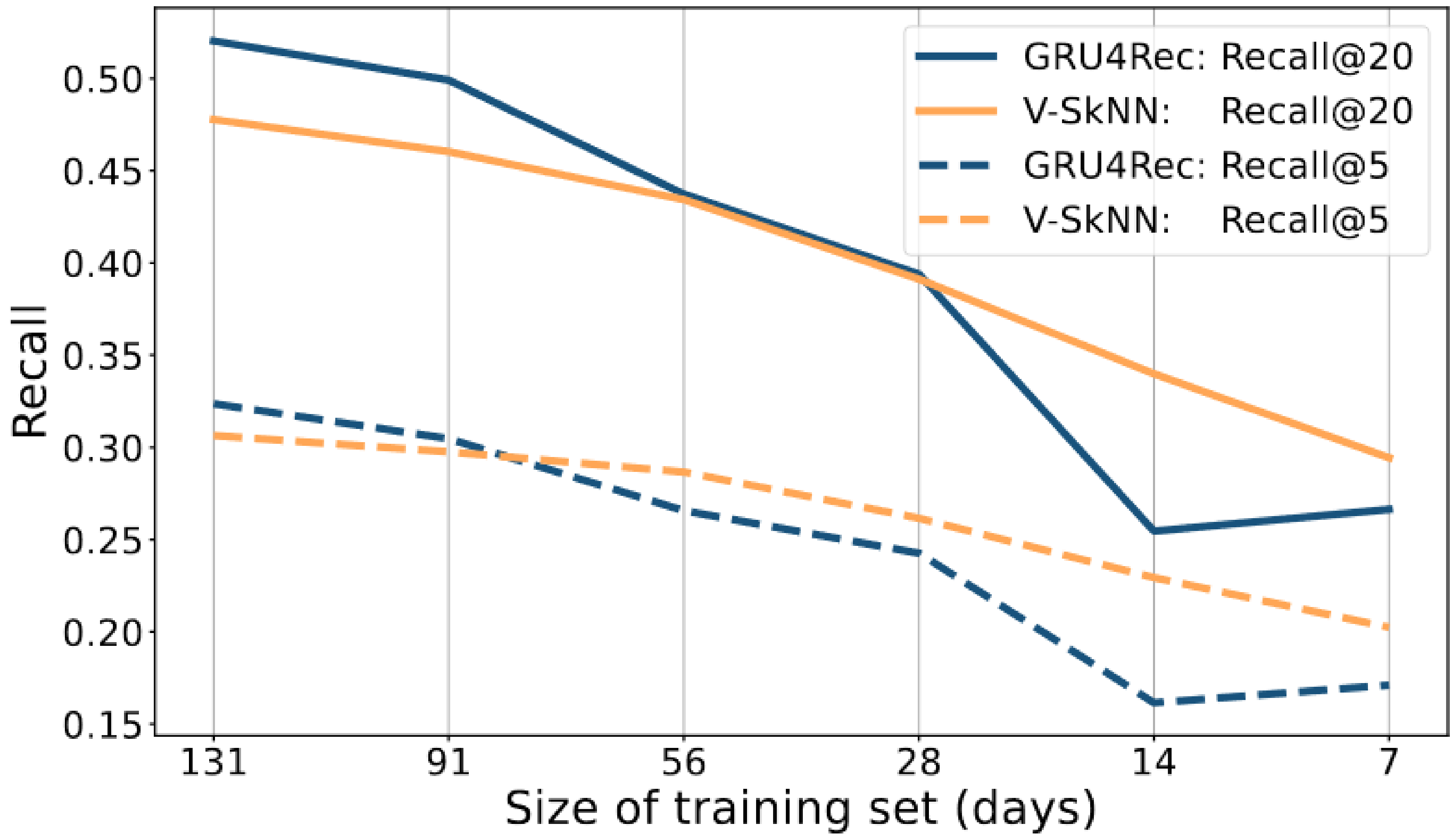
# Efectos del Preprocesamiento

- Los datos suelen tener ruido
- Considerar efectos del preprocesamiento
- La evaluación offline está sesgada
- Entre más fuerte sea el filtrado menos generales son las afirmaciones

Overzealous preprocessing

# Data training

- El tamaño del set de entrenamiento afecta el rendimiento del modelo

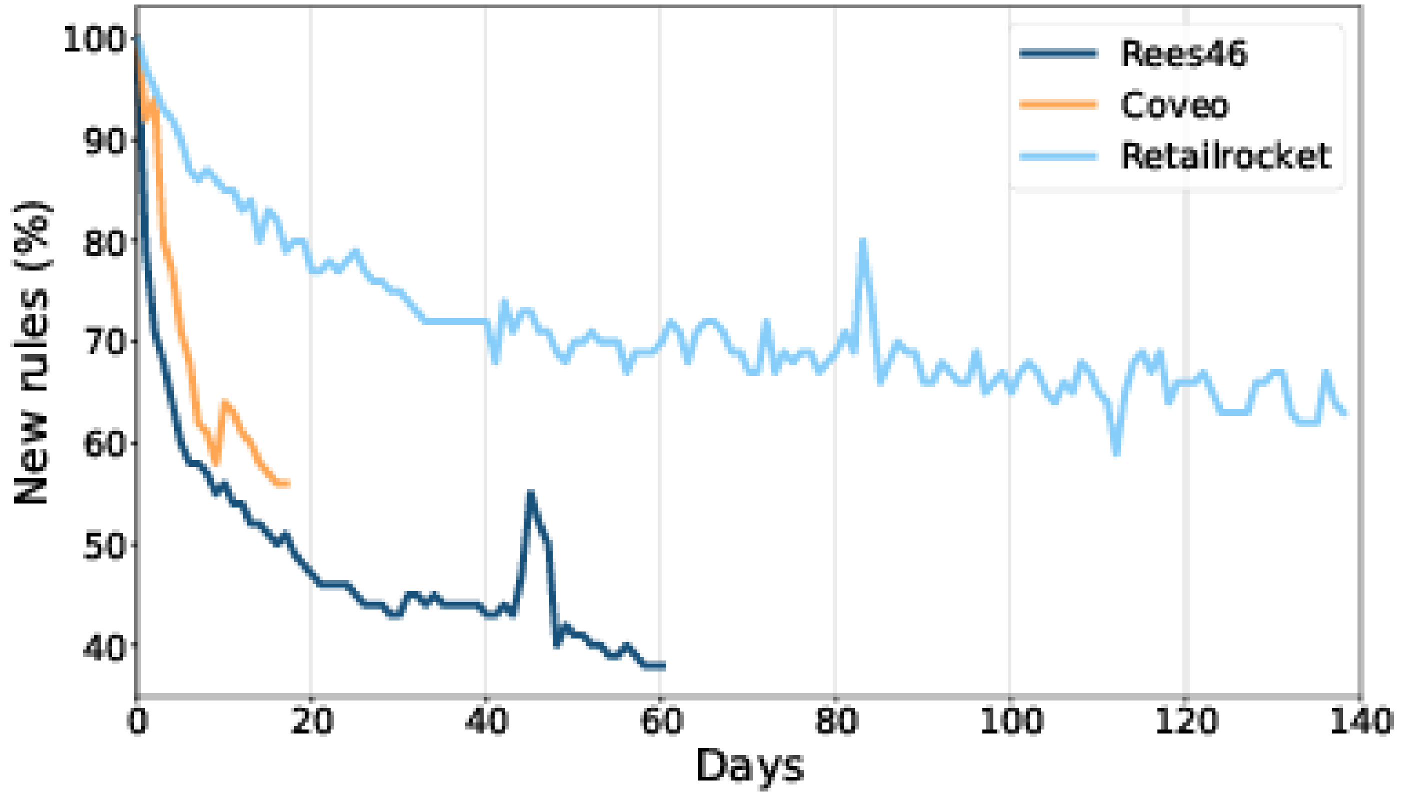


# Information leaking through time

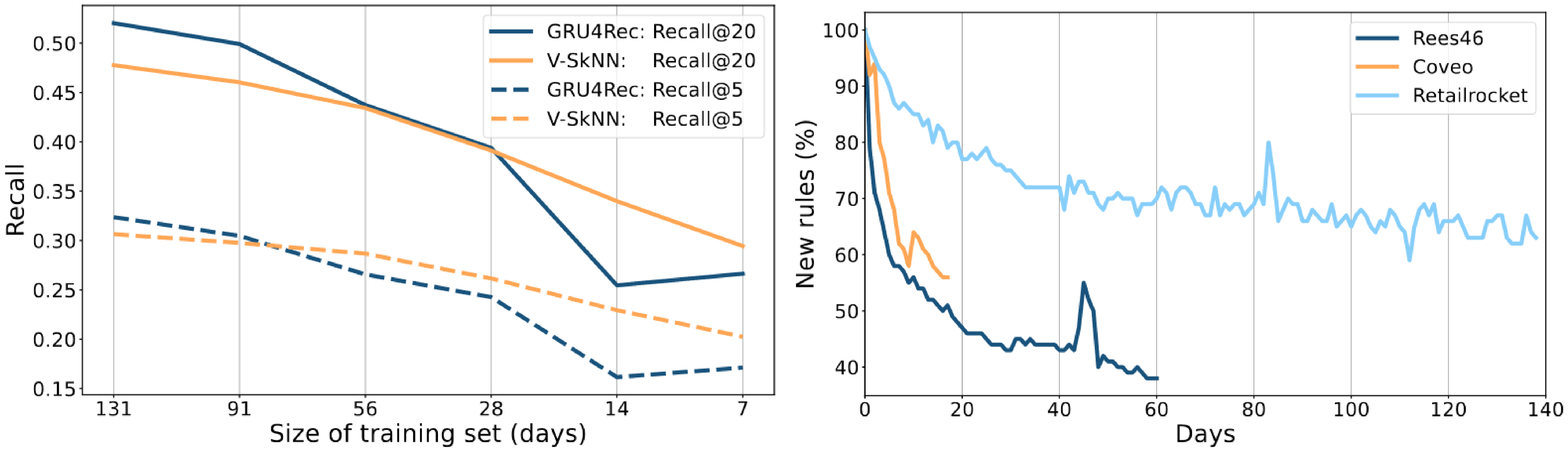
Information leaking through time

# Data training

- El tamaño del set de entrenamiento afecta el rendimiento del modelo

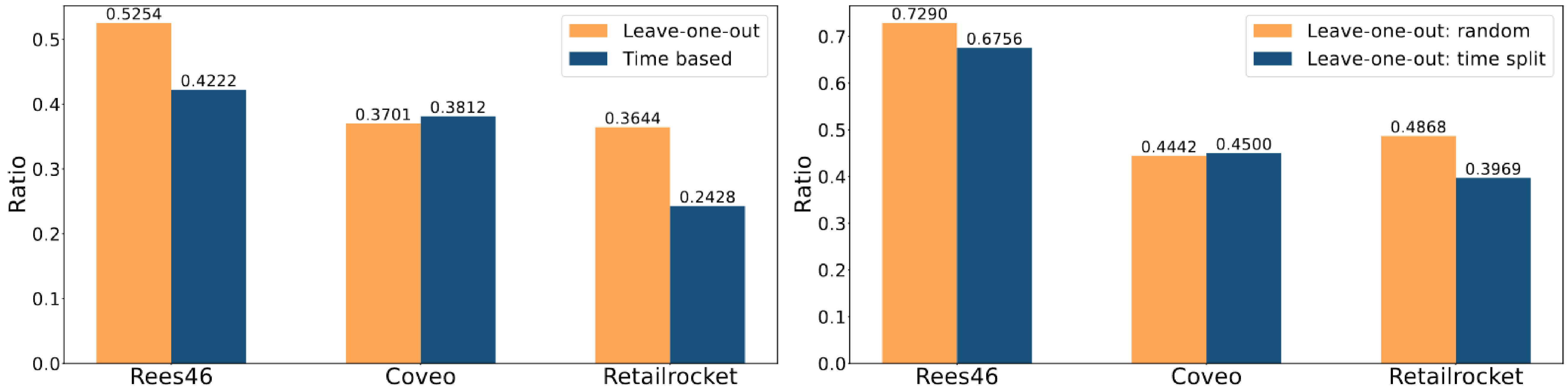



(b) Proportion of $i \to j$ item transitions observed first on day $N$ to the number of unique sequences of the same day




(a) The effect of using only recent data on the recommendation accuracy of model and neighbor based methods

(b) Proportion of $i \rightarrow j$ item transitions observed first on day $N$ to the number of unique sequences of the same day




(a) Leave-one-out and time based split

(b) Leave-one-out on random vs. most recent sessions

Fig. 2. Proportion of the $i \longrightarrow j$ test item transitions that are shared with the training set

# Negative sampling during testing

## Negative sampling during testing

# Razón de uso

- Conectado al cambio de error metrics a IR metrics
- Sampling en set de testeo
- Utilizado ampliamente

# Efectos en testing

- Sobreestimacion de metricas de evaluacion
- Cambia el ordenamiento de los modelos basado en el rendimiento

## Negative sampling during testing

# Resultados

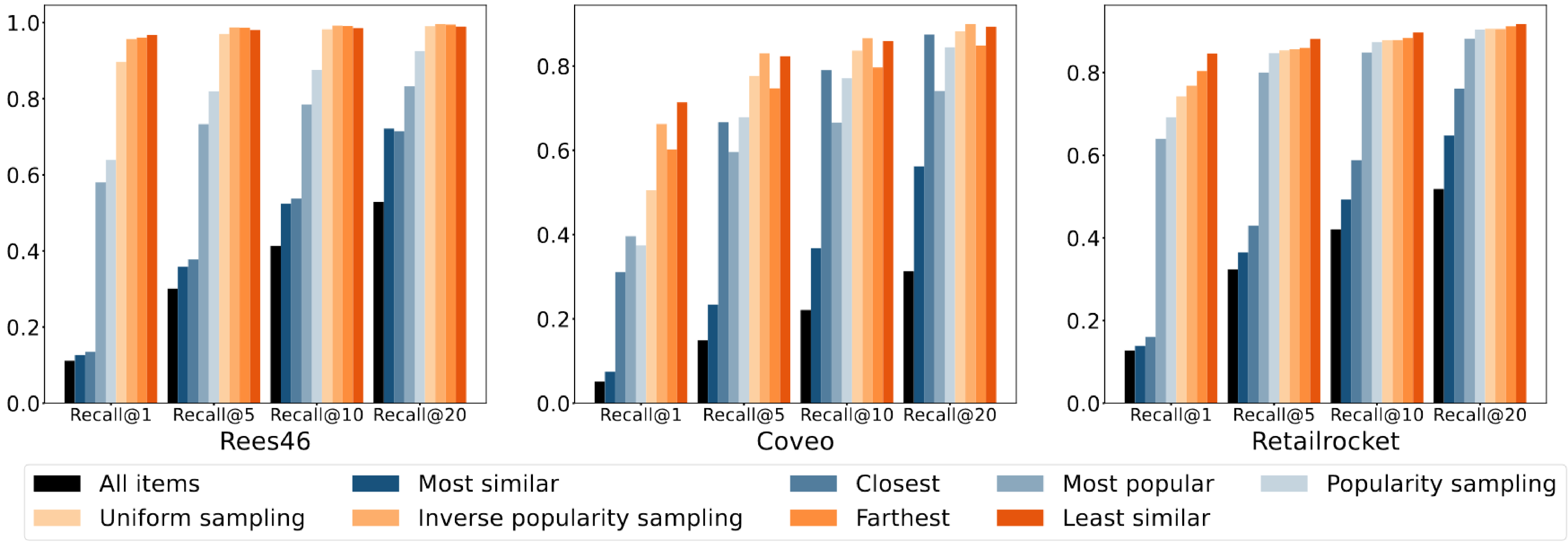


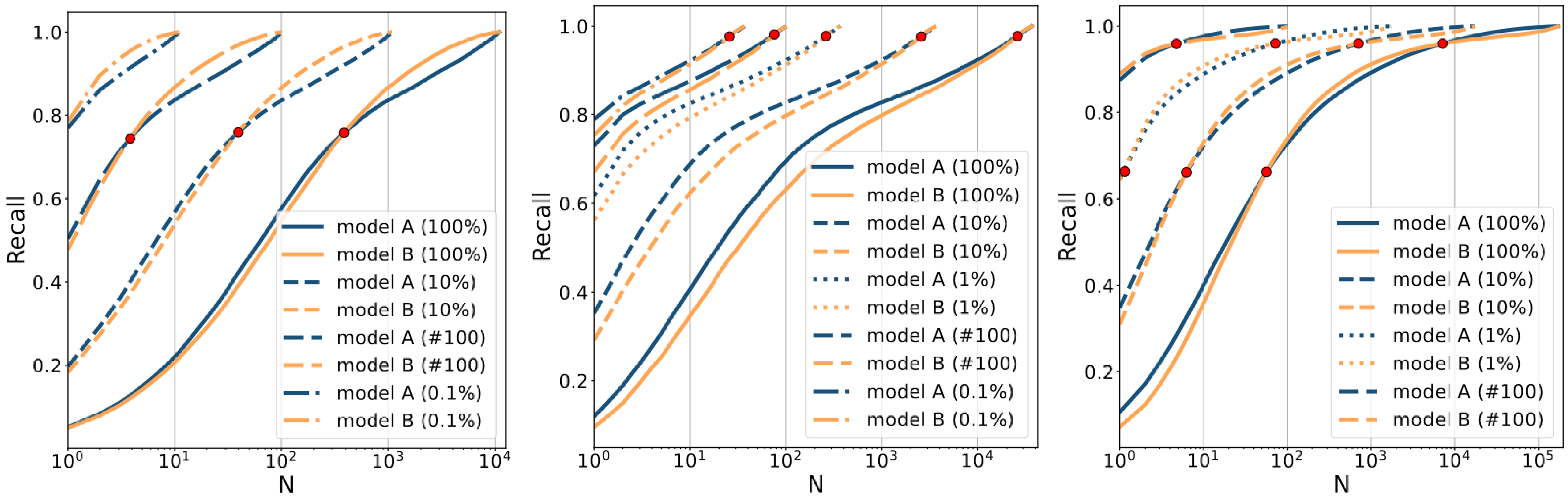

Fig. 3. Comparison of the strength of various negative samples of 100 items and no sampling.

# Resultados

- Disminucion de elementos negativos desafiantes
- Rendimiento relativo con longitud de lista de recomendación $M$ se desplaza a la longitud $N \, (\ll M)$

## Negative sampling during testing

# Resultados

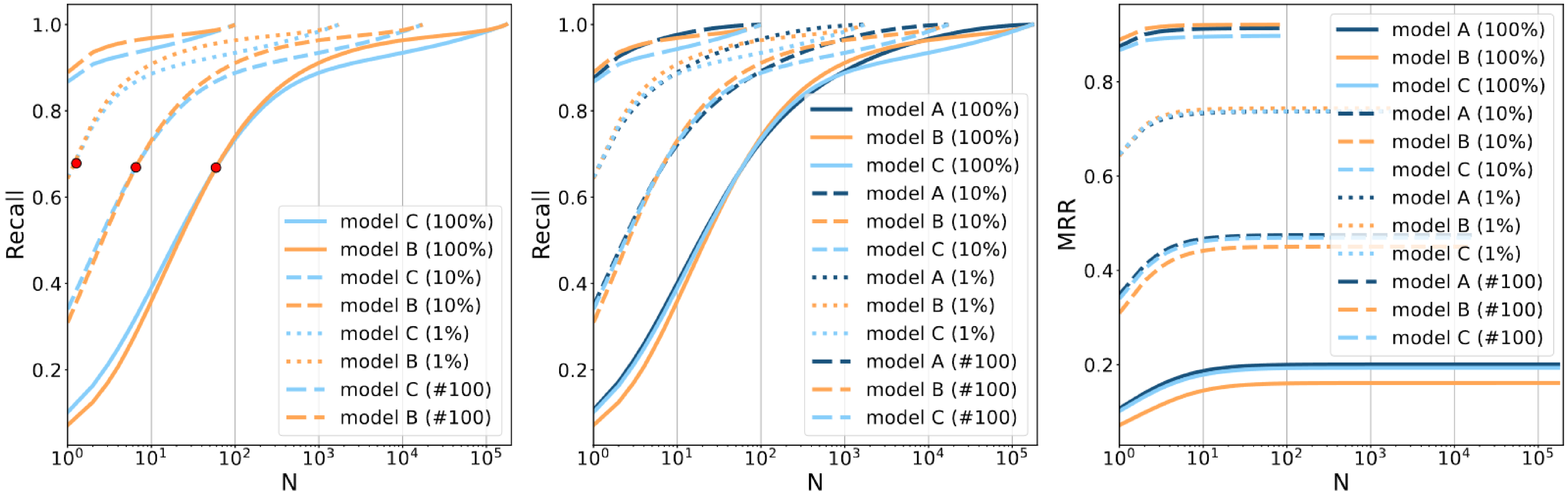



(a) Coveo – Recall@N (b) Retailrocket – Recall@N (c) Rees46 – Recall@N – AB

Fig. 4. Accuracy as the function of recommendation list length, with and without sampling

## Negative sampling during testing

# Resultados




(d) Rees46 – Recall@N – BC (e) Rees46 – Recall@N – ALL (f) Rees46 – MRR@N – ALL

Fig. 4. Accuracy as the function of recommendation list length, with and without sampling

# Trabajos Relacionados

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- La evaluacion offline ha sido discutida ampliamente
- Razon de falta de reproducibilidad actual (Ferrari, Cremonesi & Jannach, 2019 )
- Solo negative sampling ha sido estudiado (Krichene & Rendle, 2020)
- Breve mención de Dataset-Task Mismatch (Tang & Wang, 2018)

# Conclusiones

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Overzealous preprocessing

Dataset-Task Mismatch

Negative sampling during testing

Information leaking through time

# Conclusiones

Dataset-Task Mismatch

Errores que plagan a la gran mayoría de estudios

Overzealous preprocessing

Negative sampling during testing

Information leaking through time

# Conclusiones

- Por tanto, antes de establecer las métricas y métodos de evaluación de un sistema recomendador, es necesario considerar todos los problemas presentados

Conclusiones

# Referencias


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Conclusiones

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