# Comparative study of instance-level explanation methods for textual and behavioral data

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Applications using high-dimensional, sparse data are ample













#### **Behavioral data**

payment data, visited websites or physical locations, FB likes etc.

#### Textual data

emails, news articles, Twitter posts etc.

High-dimensional + sparse → Gender prediction using

ACTIVE FEATURE = "EVIDENCE" movie viewing data

		Star wars	Pearl Harbor	Django	<b>:</b>	Home Alone	Target $\widehat{y}$ Gender
10	User 1	1	0	0		1	M
6,040 users	User 2	1	1	0		1	F
6,04							
	User n	1	1	1		0	M

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- Interpretability issues: how are predictions made?

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- Model improvements eg, debugging
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**INSTANCE-LEVEL EXPLANATIONS** 

"Which model-agnostic, instance-level explanation algorithm is most suitable for explaining model predictions of classifiers built from textual/behavioral data?"



- Overview and selection of instance-level explanation methods (literature review)
- Selection of quantitative criteria
- Comparison using behavioral/textual data

#### **Selection criteria**

- Model-agnostic methods treat the model as a black-box
- Computational ability to cope with high-dimensional data

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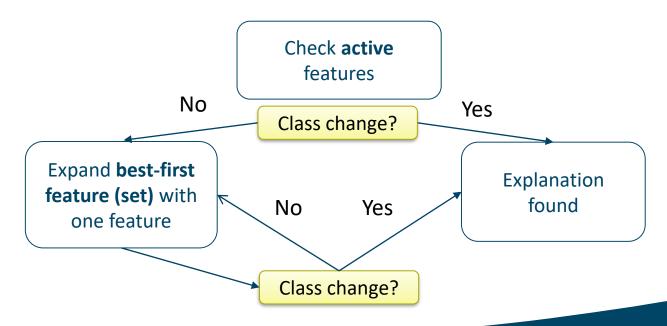


- Evidence Counterfactual (EDC) (Martens & Provost, 2013)
- Linear Interpretable Model-Agnostic Explainer (LIME) (Ribeiro et al., 2016)
- Shapley Additive Explanations (SHAP) (Lundberg & Lee, 2017)

#### **Evidence Counterfactual**

- Minimal set of features so that "removing" them results in a predicted class change
- Removing 

  set feature value to zero
- Model-agnostic algorithm (SEDC) based on heuristic best-first



## **Evidence Counterfactual – example**

Example: gender prediction using movie viewing data



User x<sub>i</sub>: Sam

Sam watched 120 movies Sam is predicted as male

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User x<sub>i</sub>: Sam

WHY?

Sam watched 120 movies Sam is predicted as male

## **Evidence Counterfactual – example**

Example: gender prediction using movie viewing data



User x<sub>i</sub>: Sam

IF Sam would not have watched {Taxi driver, The Dark Knight, Die Hard, Terminator 2, Now You See Me, Interstellar}, THEN his predicted class would change from male to female

#### **Evidence Counterfactual – example**

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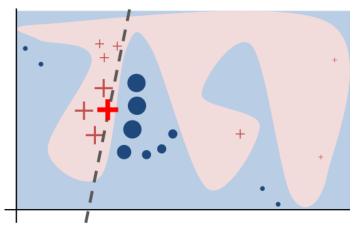
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**POSITIVE EVIDENCE = EVIDENCE FOR A PREDICTED CLASS** 

## **LIME / SHAP**

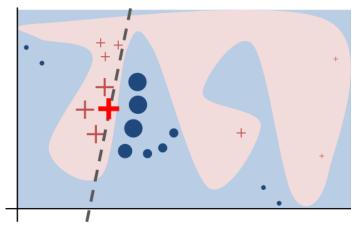
- Explanation model: sparse, linear model
- Explanation model approximates original model in the neighborhood of the instance
- Perturbed instances



Source: Ribeiro et al., 2016

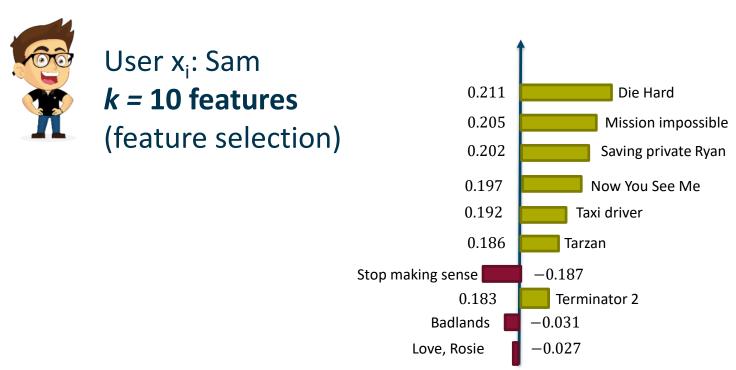
## LIME / SHAP – differences

- How they generate perturbed samples
- Distance function
- Complexity control

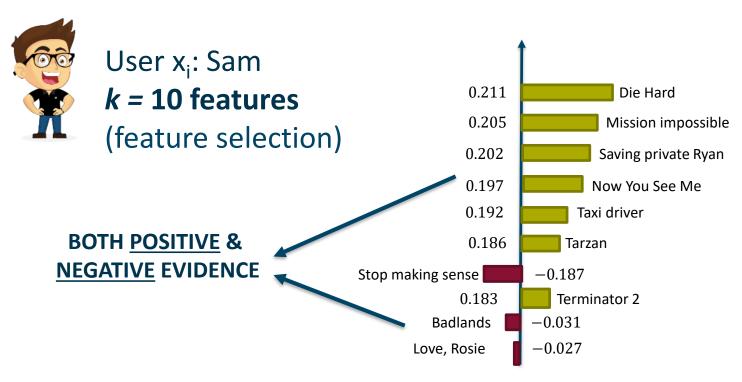


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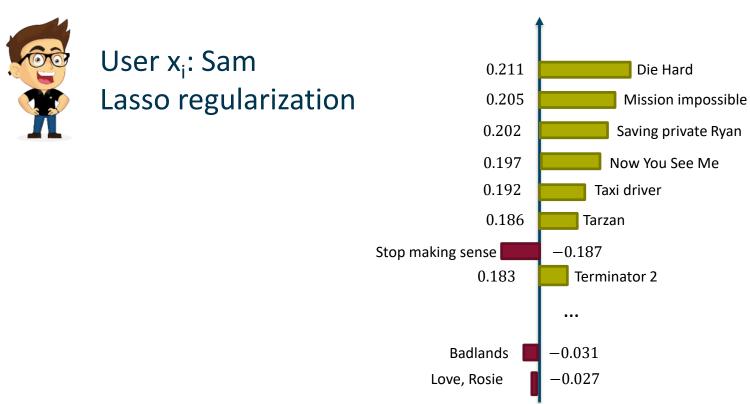
## LIME – example



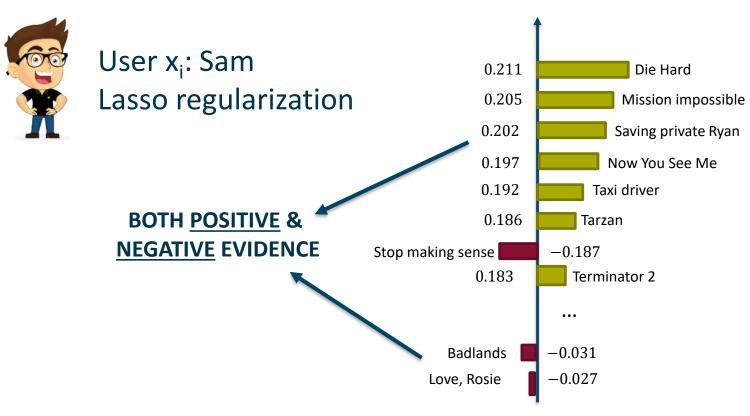
## LIME – example



## SHAP – example



#### SHAP – example



# 3. EVALUATION CRITERIA

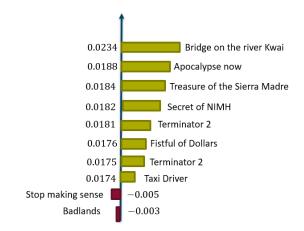
- ⇒ **NOT** a **qualitative** evaluation
- ⇒ No evaluation of *counterfactual* versus *linear model*, *negative* evidence, *output size* etc.

VS

#### **Counterfactual**

IF Sam would not have rated {Taxi driver, North by Northwest, Bridge on the river Kwai, Terminator 2, Hunt for red October, Glengarry Glen Ross}, THEN his predicted class would change from male to female

#### Additive feature attribution





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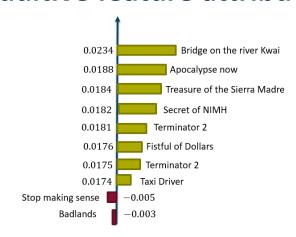
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⇒ Quantitative evaluation

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# 3. EVALUATION CRITERIA

#### 1. Effectiveness

- **Switching point**: number of features (with positive weight) that need to be removed before the classification changes
- % of switching points found
- % generated output
- Output size

#### 2. Efficiency

Computation time: number of seconds to generate explanation

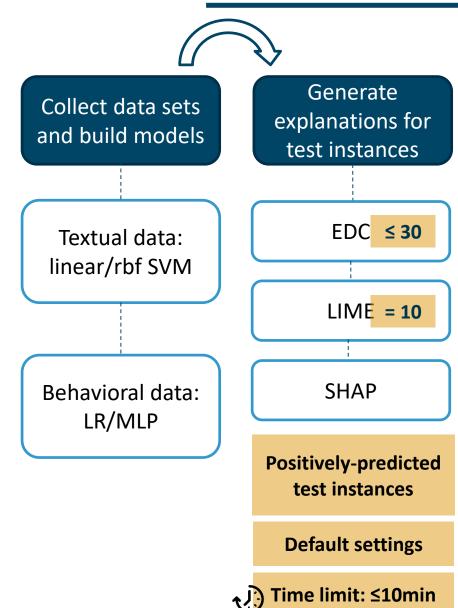
Collect data sets and build models

Textual data: linear/rbf SVM

Behavioral data: LR/MLP

**Table 1: Data sets and characteristics** 

Dataset	$\mathbf{Type}$	$\mathbf{Target}$	Instances	Features	b	p
Movielens_1m*	В	gender	6,040	3,706	28.29%	95.5316%
Movielens_100k	В	gender	943	1,682	28.95%	93.6953%
YahooMovies*	В	gender	7,642	11,915	28.87%	99.7596%
Ecommerce*	В	gender	15,000	21,880	21.98%	99.9898%
Facebook*	В	gender	386,321	122,924	44.57%	99.9416%
KDD2015*	В	dropout	120,542	4,835	20.71%	99.6707%
Fraud*	В	fraudulent	858,131	107,345	0.000064%	99.9979%
TaFeng*	В	age	31,640	23,719	45.23%	99.9036%
Flickr*	В	comments	100,000	190,991	36.91%	99.9877%
LibimSeTi*	В	gender	137,806	166,353	44.53%	99.9317%
20news	${ m T}$	atheism	18,846	41,356	4.24%	99.8435%
Airline*	${ m T}$	sentiment	14,640	5,183	16.14%	99.8191%
Twitter	${ m T}$	$_{ m topic}$	6,090	4,569	9.15%	99.7428%



Collect data sets and build models

Textual data: linear/rbf SVM

Behavioral data: LR/MLP Generate explanations for test instances

EDC **≤ 30** 

LIME = **10** 

**SHAP** 

Positively-predicted test instances

**Default settings** 

**Time limit: ≤10min** 

**Evaluation** 

% generated output

Output size

Computation time

Switching point

% switching point found

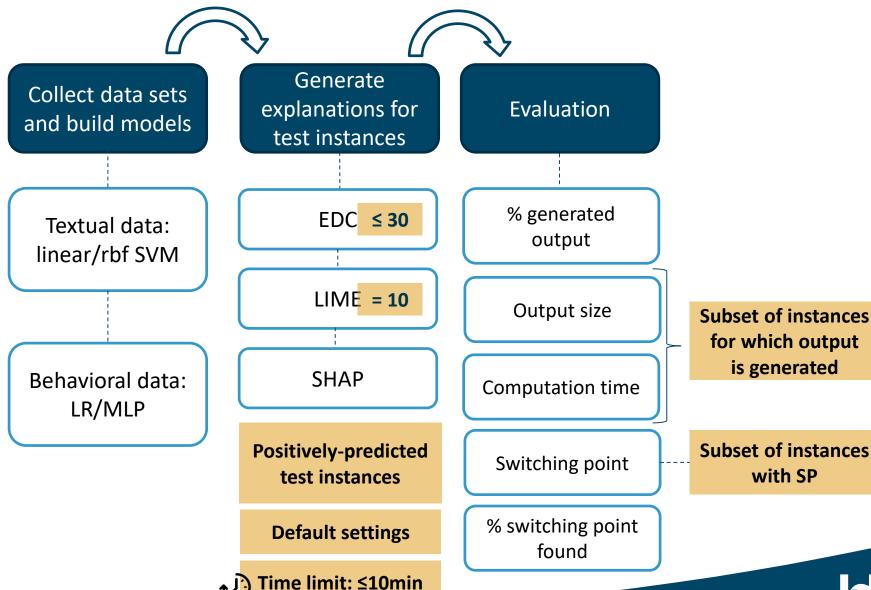


Table 4: Percentage of generated output. For stochastic LIME/SHAP, this are average percentages over 5 runs. The best percentages are indicated in bold. The percentages are underlined if a method is significantly worse than the best method on a 1% significance level using a McNemar mid-p test [17].

		Linear			Nonlinear	
Dataset	<b>EDC</b> (%)	LIME $(\%)$	$\mathbf{SHAP}\ (\%)$	<b>EDC</b> (%)	LIME $(\%)$	SHAP $(\%)$
Movielens_1m	98.67	100	100	89.67	100	100
$Movielens_100k$	100	100	100	100	100	100
YahooMovies	100	100	100	98.67	100	100
Ecommerce	100	100	100	95	100	100
Facebook	96.67	100	100	70.33	100	100
KDD2015	100	100	100	99.67	100	100
Fraud	100	100	81.67	100	100	<u>75</u>
TaFeng	100	100	100	93.33	100	100
Flickr	100	100	100	100	100	100
LibimSeTi	95.67	100	100	77.33	100	100
20news	100	100	100	100	100	100
Airline	100	100	100	100	100	100
Twitter	100	100	100	100	100	100
Average	99.31	100	98.59	88.67	100	98.08
# wins	10	13	12	6	13	12

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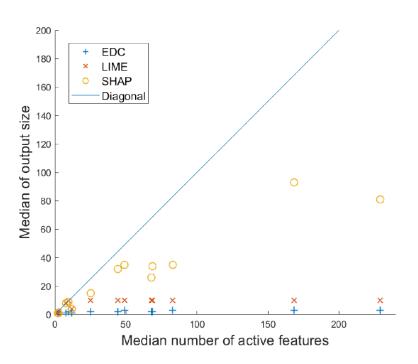
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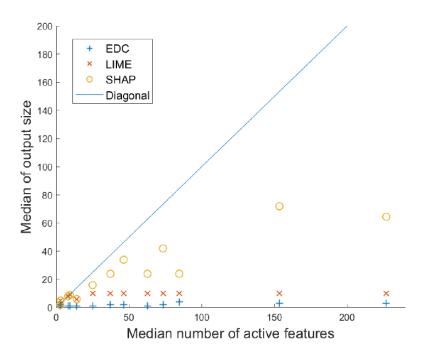


Fig. 2: Median of output size for linear (right) and nonlinear (left) models as a function of median number of active features.

Table 2: Percentage of switching points found (smaller than 30). For stochastic LIME/SHAP, these are average percentages over 5 runs. The best percentages are indicated in bold. The percentages are underlined if a method is significantly worse than the best method on a 1% significance level using a McNemar mid-p test [17].

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Ecommerce	100	97.33	100	95.00	96.67	$\boldsymbol{99.67}$
Facebook	$\boldsymbol{96.67}$	95.33	95.00	70.33	$\overline{93.67}$	90.00
KDD2015	100	100	100	99.67	100	99.67
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TaFeng	100	100	100	93.33	100	$\overline{100}$
Flickr	100	99.33	100	28.67	28.67	<b>28.67</b>
LibimSeTi	$\boldsymbol{95.67}$	91.00	89.33	77.33	91.33	89.67
20news	100	99.47	100	100	98.94	100
Airline	100	100	100	100	100	100
Twitter	100	100	100	100	100	100
Average	99.31	98.55	97.28	88.67	92.69	90.64
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**Table 3:** Median and interquantile range of **absolute switching point** with corresponding relative predicted score change. For stochastic LIME/SHAP, this is the average median/range over 5 runs. The switching point is measured over the subset of instances where *all* methods have found a switching point. The best (median) absolute switching points are indicated in bold. The values are underlined if a method is significantly worse than the best method on a 1% significance level using a McNemar mid-p test [17].

		Linear				Nonlinear		
Dataset	EDC	LIME	SHAP	Random	EDC	LIME	$\mathbf{SHAP}$	Random
Movielens_1m	3(2-7)	3(2-7)	3(2-7)	9(4-19)	3(1-6)	3(2-8)	3(2-8)	7(3-14.5)
$Movielens\_100k$	2(1-4)	2(1-4)	2(1-4)	$\overline{5.5(3-10)}$	2(1-4)	2(1-4)	2(1-4)	$\overline{5(2-9.75)}$
YahooMovies	2(1-4)	2(1-4)	2(1-4)	4(2-7)	1(1-3)	2(1-3)	2(1-3)	4(2-12)
Ecommerce	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1\text{-}2)}$	1(1-1)	$\overline{1(1\text{-}1)}$	1(1-1)	$\overline{1(1-1)}$
Facebook	3(2-8)	4(2-8.6)	4(2-8)	8(4-20)	4.5(1-13.25)	4(2-9.2)	4.4(2-10.4)	9.5(4-20)
KDD2015	3(1-7)	3(1-7)	$\overline{3(1-7)}$	8(3-17)	2(1-3)	2(1-3.8)	2(1-4)	4.5(2-9)
Fraud	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1-1)}$	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1-2)}$
$\operatorname{TaFeng}$	2(1-4)	2(1-4)	2(1-4)	5(3-11)	2(1-8)	2(1-3)	2(1-4)	6(3-17)
Flickr	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1\text{-}1)}$	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1-2)}$
Libimseti	3(2-7)	3(2-8.2)	3(2-7.4)	30(13.75 - 55)	2.5(1-5)	3(2-8.2)	3(2-7.2)	22(9.75 - 43.25)
20news	2(1-4)	2(1-4)	2(1-4)	11(4-24)	1(1-3)	$\overline{1(1\text{-}3)}$	$\overline{1(1\text{-}3)}$	8(3-19)
Airline	1(1-2)	1(1-2)	1(1-2)	2(1-3)	1(1-1)	1(1-1)	1(1-1)	2(1-3)
Twitter	2(1-3)	2(1-3)	2(1-3)	3(2-5)	1(1-1)	1(1-1)	1(1-1)	3(2-5.5)
# wins	13	12	12	3	12	11	10	3

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		Linear				Nonlinear		
Dataset	$\mathbf{EDC}$	LIME	SHAP	Random	EDC	LIME	$\mathbf{SHAP}$	Random
Movielens_1m	3(2-7)	3(2-7)	3(2-7)	9(4-19)	3(1-6)	3(2-8)	3(2-8)	7(3-14.5)
Movielens_100k	2(1-4)	2(1-4)	2(1-4)	$\overline{5.5(3-10)}$	2(1-4)	2(1-4)	2(1-4)	$\overline{5(2-9.75)}$
YahooMovies	2(1-4)	2(1-4)	2(1-4)	4(2-7)	1(1-3)	2(1-3)	2(1-3)	4(2-12)
Ecommerce	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1\text{-}2)}$	1(1-1)	$\overline{1(1\text{-}1)}$	1(1-1)	$\overline{1(1\text{-}1)}$
Facebook	3(2-8)	4(2-8.6)	4(2-8)	8(4-20)	4.5(1-13.25)	4(2-9.2)	4.4(2-10.4)	9.5(4-20)
KDD2015	3(1-7)	3(1-7)	$\overline{3(1-7)}$	8(3-17)	2(1-3)	2(1-3.8)	2(1-4)	4.5(2-9)
Fraud	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1\text{-}1)}$	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1-2)}$
$\operatorname{TaFeng}$	2(1-4)	2(1-4)	2(1-4)	5(3-11)	2(1-8)	2(1-3)	2(1-4)	6(3-17)
Flickr	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1\text{-}1)}$	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1\text{-}2)}$
(Libimseti)	3(2-7)	3(2-8.2)	3(2 - 7.4)	30(13.75 - 55)	2.5(1-5)	3(2-8.2)	3(2-7.2)	22(9.75 - 43.25)
20news	2(1-4)	2(1-4)	2(1-4)	11(4-24)	1(1-3)	$\overline{1(1\text{-}3)}$	$\overline{1(1\text{-}3)}$	8(3-19)
Airline	1(1-2)	1(1-2)	1(1-2)	2(1-3)	1(1-1)	1(1-1)	1(1-1)	2(1-3)
Twitter	2(1-3)	2(1-3)	2(1-3)	3(2-5)	1(1-1)	1(1-1)	1(1-1)	3(2-5.5)
# wins	13	12	12	3	12	11	10	3

**Table 3:** Median and interquantile range of **absolute switching point** with corresponding relative predicted score change. For stochastic LIME/SHAP, this is the average median/range over 5 runs. The switching point is measured over the subset of instances where *all* methods have found a switching point. The best (median) absolute switching points are indicated in bold. The values are underlined if a method is significantly worse than the best method on a 1% significance level using a McNemar mid-p test [17].

1		Linear				Nonlinear		
Dataset	EDC	LIME	SHAP	Random	EDC	LIME	SHAP	Random
Movielens_1m	3(2-7)	3(2-7)	3(2-7)	9(4-19)	3(1-6)	3(2-8)	3(2-8)	7(3-14.5)
$Movielens\_100k$	2(1-4)	2(1-4)	2(1-4)	$\overline{5.5(3-10)}$	2(1-4)	2(1-4)	2(1-4)	$\overline{5(2-9.75)}$
YahooMovies	2(1-4)	2(1-4)	2(1-4)	4(2-7)	1(1-3)	2(1-3)	2(1-3)	4(2-12)
Ecommerce	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1\text{-}2)}$	1(1-1)	$\overline{1(1\text{-}1)}$	1(1-1)	$\overline{1(1-1)}$
Facebook	3(2-8)	4(2-8.6)	4(2-8)	8(4-20)	4.5(1-13.25)	4(2-9.2)	4.4(2-10.4)	9.5(4-20)
KDD2015	3(1-7)	3(1-7)	$\overline{3(1-7)}$	8(3-17)	2(1-3)	2(1-3.8)	2(1-4)	4.5(2-9)
Fraud	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1-1)}$	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1-2)}$
TaFeng	2(1-4)	2(1-4)	2(1-4)	5(3-11)	2(1-8)	2(1-3)	2(1-4)	6(3-17)
Flickr	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1\text{-}1)}$	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1-2)}$
Libimseti	3(2-7)	3(2-8.2)	3(2-7.4)	30(13.75 - 55)	2.5(1-5)	3(2-8.2)	3(2-7.2)	22(9.75 - 43.25)
20news	2(1-4)	2(1-4)	2(1-4)	11(4-24)	1(1-3)	$\overline{1(1\text{-}3)}$	$\overline{1(1\text{-}3)}$	8(3-19)
Airline	1(1-2)	1(1-2)	1(1-2)	2(1-3)	1(1-1)	1(1-1)	1(1-1)	2(1-3)
Twitter	2(1-3)	2(1-3)	2(1-3)	3(2-5)	1(1-1)	1(1-1)	1(1-1)	3(2-5.5)
# wins	13	12	12	3	12	11	10	3

**Table 3:** Median and interquantile range of **absolute switching point** with corresponding relative predicted score change. For stochastic LIME/SHAP, this is the average median/range over 5 runs. The switching point is measured over the subset of instances where *all* methods have found a switching point. The best (median) absolute switching points are indicated in bold. The values are underlined if a method is significantly worse than the best method on a 1% significance level using a McNemar mid-p test [17].

		Linear				Nonlinear		
Dataset	$\mathbf{EDC}$	$\mathbf{LIME}$	$\mathbf{SHAP}$	$\mathbf{Random}$	EDC	LIME	$\mathbf{SHAP}$	Random
Movielens_1m	3(2-7)	3(2-7)	3(2-7)	9(4-19)	3(1-6)	3(2-8)	3(2-8)	7(3-14.5)
$Movielens\_100k$	2(1-4)	2(1-4)	2(1-4)	$\overline{5.5(3-10)}$	2(1-4)	2(1-4)	2(1-4)	$\overline{5(2-9.75)}$
YahooMovies	2(1-4)	2(1-4)	2(1-4)	4(2-7)	1(1-3)	2(1-3)	2(1-3)	4(2-12)
Ecommerce	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1-2)}$	1(1-1)	$\overline{1(1\text{-}1)}$	1(1-1)	$\overline{1(1-1)}$
Facebook	3(2-8)	4(2-8.6)	4(2-8)	8(4-20)	4.5(1-13.25)	1(2-9.2)	4.4(2-10.4)	9.5(4-20)
KDD2015	3(1-7)	3(1-7)	$\overline{3(1-7)}$	8(3-17)	2(1-3)	2(1-3.8)	2(1-4)	4.5(2-9)
Fraud	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1-1)}$	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1-2)}$
TaFeng	2(1-4)	2(1-4)	2(1-4)	5(3-11)	2(1-8)	2(1-3)	2(1-4)	6(3-17)
Flickr	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1\text{-}1)}$	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1-2)}$
Libimseti	3(2-7)	3(2-8.2)	3(2-7.4)	30(13.75 - 55)	2.5(1-5)	3(2-8.2)	3(2-7.2)	22(9.75 - 43.25)
20news	2(1-4)	2(1-4)	2(1-4)	11(4-24)	1(1-3)	$\overline{1(1\text{-}3)}$	$\overline{1(1\text{-}3)}$	8(3-19)
Airline	1(1-2)	1(1-2)	1(1-2)	2(1-3)	1(1-1)	1(1-1)	1(1-1)	2(1-3)
Twitter	2(1-3)	2(1-3)	2(1-3)	3(2-5)	1(1-1)	1(1-1)	1(1-1)	3(2-5.5)
# wins	13	12	12	3	12	11	10	3

**Table 3:** Median and interquantile range of **absolute switching point** with corresponding relative predicted score change. For stochastic LIME/SHAP, this is the average median/range over 5 runs. The switching point is measured over the subset of instances where *all* methods have found a switching point. The best (median) absolute switching points are indicated in bold. The values are underlined if a method is significantly worse than the best method on a 1% significance level using a McNemar mid-p test [17].

		Linear				Nonlinear		
Dataset	$\mathbf{EDC}$	$\mathbf{LIME}$	$\mathbf{SHAP}$	Random	EDC	LIME	$\mathbf{SHAP}$	Random
Movielens_1m	3(2-7)	3(2-7)	3(2-7)	9(4-19)	3(1-6)	3(2-8)	3(2-8)	7(3-14.5)
$Movielens\_100k$	2(1-4)	2(1-4)	2(1-4)	$\overline{5.5(3-10)}$	2(1-4)	2(1-4)	$\frac{2(1-4)}{}$	$\overline{5(2-9.75)}$
YahooMovies	2(1-4)	2(1-4)	2(1-4)	4(2-7)	1(1-3)	2(1-3)	2(1-3)	4(2-12)
Ecommerce	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1\text{-}2)}$	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1\text{-}1)}$
Facebook	3(2-8)	4(2-8.6)	4(2-8)	8(4-20)	4.5(1-13.25)	4(2-9.2)	4.4(2-10.4)	9.5(4-20)
KDD2015	3(1-7)	3(1-7)	$\overline{3(1-7)}$	8(3-17)	2(1-3)	2(1-3.8)	$\overline{2(1-4)}$	4.5(2-9)
Fraud	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1-1)}$	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1-2)}$
$\operatorname{TaFeng}$	2(1-4)	2(1-4)	2(1-4)	5(3-11)	2(1-8)	2(1-3)	2(1-4)	6(3-17)
Flickr	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1\text{-}1)}$	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1-2)}$
Libimseti	3(2-7)	3(2-8.2)	3(2-7.4)	30(13.75 - 55)	2.5(1-5)	3(2-8.2)	3(2-7.2)	22(9.75 - 43.25)
20news	2(1-4)	2(1-4)	2(1-4)	11(4-24)	1(1-3)	1(1-3)	1(1-3)	8(3-19)
Airline	1(1-2)	1(1-2)	1(1-2)	2(1-3)	1(1-1)	1(1-1)	1(1-1)	2(1-3)
Twitter	2(1-3)	2(1-3)	2(1-3)	3(2-5)	1(1-1)	1(1-1)	1(1-1)	3(2-5.5)
# wins	13	12	12	3	12	11	10	3

**Table 3:** Median and interquantile range of **absolute switching point** with corresponding relative predicted score change. For stochastic LIME/SHAP, this is the average median/range over 5 runs. The switching point is measured over the subset of instances where *all* methods have found a switching point. The best (median) absolute switching points are indicated in bold. The values are underlined if a method is significantly worse than the best method on a 1% significance level using a McNemar mid-p test [17].

		Linear				Nonlinear		
Dataset	EDC	LIME	SHAP	Random	EDC	LIME	SHAP (	Random
Movielens_1m	3(2-7)	3(2-7)	3(2-7)	9(4-19)	3(1-6)	3(2-8)	3(2-8)	7(3-14.5)
$Movielens_100k$	2(1-4)	2(1-4)	2(1-4)	$\overline{5.5(3-10)}$	2(1-4)	2(1-4)	2(1-4)	$\overline{5(2-9.75)}$
YahooMovies	2(1-4)	2(1-4)	2(1-4)	4(2-7)	1(1-3)	2(1-3)	2(1-3)	4(2-12)
Ecommerce	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1\text{-}2)}$	1(1-1)	$\overline{1(1\text{-}1)}$	1(1-1)	$\overline{1(1-1)}$
Facebook	3(2-8)	4(2-8.6)	4(2-8)	8(4-20)	4.5(1-13.25)	4(2-9.2)	4.4(2-10.4)	9.5(4-20)
KDD2015	3(1-7)	3(1-7)	$\overline{3(1-7)}$	8(3-17)	2(1-3)	2(1-3.8)	2(1-4)	4.5(2-9)
Fraud	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1-1)}$	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1-2)}$
TaFeng	2(1-4)	2(1-4)	2(1-4)	5(3-11)	2(1-8)	2(1-3)	2(1-4)	6(3-17)
Flickr	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1\text{-}1)}$	1(1-1)	1(1-1)	1(1-1)	$\overline{1(1-2)}$
Libimseti	3(2-7)	3(2-8.2)	3(2-7.4)	30(13.75 - 55)	2.5(1-5)	3(2-8.2)	3(2-7.2)	22(9.75 - 43.25)
20news	2(1-4)	2(1-4)	2(1-4)	11(4-24)	1(1-3)	$\overline{1(1\text{-}3)}$	$\overline{1(1-3)}$	8(3-19)
Airline	1(1-2)	1(1-2)	1(1-2)	2(1-3)	1(1-1)	1(1-1)	1(1-1)	2(1-3)
Twitter	2(1-3)	2(1-3)	2(1-3)	3(2-5)	1(1-1)	1(1-1)	1(1-1)	3(2-5.5)
# wins	13	12	12	3	12	11	10	3

Table 5: Median and interquantile range of computation time in seconds. For stochastic LIME/SHAP, this is the average median/range over 5 runs. The best (median) computation times are indicated in bold. The values are underlined if a method is **significantly worse than** the best method on a 1% significance level using a McNemar mid-p test [17].

		Linear			Nonlinear	
Dataset	EDC	LIME	$\operatorname{SHAP}$	EDC	LIME	$\operatorname{SHAP}$
Ecommerce	0.00(0.00 - 0.01)	0.22(0.19 - 0.24)	0.00(0.00 - 0.01)	0.00(0.00 - 0.02)	0.27(0.26 - 0.28)	0.01(0.01 - 0.01)
Facebook	0.11(0.02 - 1.19)	$\overline{0.35(0.28 - 0.51)}$	0.90(0.84 - 1.03)	0.17(0.02 - 2.03)	$\overline{0.39(0.32 - 0.55)}$	$\overline{0.95(0.88 - 1.07)}$
Flickr	0.00(0.00 - 0.00)	0.19(0.19 - 0.23)	$\overline{0.01(0.00-0.01)}$	0.00(0.00 - 0.02)	0.24(0.23 - 0.25)	$\overline{0.01(0.01-0.08)}$
Fraud	0.00(0.00 - 0.02)	$\overline{0.24(0.22-0.28)}$	$\overline{0.02(0.01-0.17)}$	0.02(0.02 - 0.02)	0.65(0.60 - 0.72)	0.05(0.02 - 0.82)
KDD2015	0.09(0.02 - 0.74)	$\overline{0.36(0.32 - 0.43)}$	$\overline{0.87(0.82 - 0.92)}$	0.14(0.03 - 0.53)	$\overline{0.57(0.52 - 0.64)}$	$\overline{1.07(1.02 - 1.13)}$
Libimseti	0.37(0.13 - 3.12)	0.70(0.59 - 0.97)	$\overline{1.17(1.09 - 1.38)}$	0.84(0.19 - 3.48)	$\overline{0.71(0.58 - 0.97)}$	$\overline{1.18(1.09 - 1.39)}$
$Movielens_1m$	0.34(0.06 - 2.92)	$\overline{0.56(0.35 - 0.99)}$	$\overline{1.06(0.30 - 1.39)}$	0.35(0.06 - 1.59)	0.72(0.51 - 1.24)	$\overline{2.49(2.21-3.33)}$
TaFeng	0.05(0.02 - 0.19)	$\overline{0.53(0.43 - 0.63)}$	$\overline{1.99(1.68 - 2.27)}$	0.03(0.02 - 0.39)	0.55(0.47 - 0.68)	1.45(1.26 - 1.63)
$Movielens_100k$	0.07(0.02 - 0.32)	$\overline{0.35(0.31 - 0.57)}$	$\overline{0.87(0.83 - 1.04)}$	0.14(0.07 - 0.70)	$\overline{0.42(0.34 - 0.66)}$	$\overline{0.93(0.88-1.13)}$
YahooMovies	0.07(0.02 - 0.19)	$\overline{0.27(0.26 - 0.31)}$	$\overline{0.80(0.77 - 0.83)}$	0.09(0.04 - 0.30)	0.63(0.62 - 0.67)	$\overline{1.11(1.08 - 1.16)}$
20news	0.19(0.05-1.43)	2.95(1.88 - 3.96)	3.36(2.49 - 4.16)	0.10(0.03 - 0.76)	$\overline{1.94(1.34 - 2.69)}$	2.39(1.88 - 2.95)
Airline	0.02(0.01 - 0.04)	$\overline{0.79(0.62 - 0.91)}$	$\overline{0.08(0.02 - 0.59)}$	0.02(0.02 - 0.03)	$\overline{1.18(0.96 - 1.33)}$	$\overline{0.10(0.02 - 0.79)}$
Twitter	0.03(0.01 - 0.05)	1.21(1.09 - 1.32)	0.37(0.09 - 1.09)	0.01(0.01 - 0.01)	0.89(0.82 - 0.95)	0.13(0.03 - 0.43)
# wins	13	0	0	13	0	0

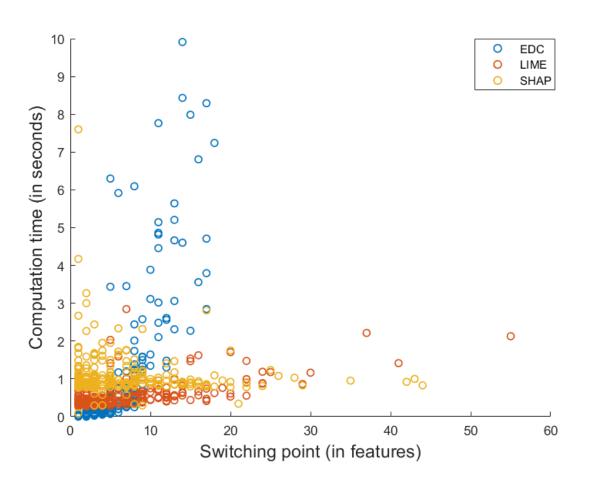
Table 5: Median and interquantile range of computation time in seconds. For stochastic LIME/SHAP, this is the average median/range over 5 runs. The best (median) computation times are indicated in bold. The values are underlined if a method is **significantly worse than** the best method on a 1% significance level using a McNemar mid-p test [17].

		Linear			Nonlinear	
Dataset	EDC	LIME	$\mathbf{SHAP}$	EDC	LIME	$\mathbf{SHAP}$
Ecommerce	0.00(0.00-0.01)	0.22(0.19 - 0.24)	0.00(0.00 - 0.01)	0.00(0.00-0.02)	0.27(0.26 - 0.28)	0.01(0.01 - 0.01)
Facebook	0.11(0.02-1.19)	$\overline{0.35(0.28 - 0.51)}$	0.90(0.84 - 1.03)	0.17(0.02 - 2.03)	$\overline{0.39(0.32 - 0.55)}$	$\overline{0.95(0.88 - 1.07)}$
Flickr	0.00(0.00 - 0.00)	0.19(0.19 - 0.23)	$\overline{0.01(0.00-0.01)}$	0.00(0.00 - 0.02)	0.24(0.23 - 0.25)	$\overline{0.01(0.01 - 0.08)}$
Fraud	0.00(0.00 - 0.02)	$\overline{0.24(0.22-0.28)}$	$\overline{0.02(0.01-0.17)}$	0.02(0.02 - 0.02)	0.65(0.60 - 0.72)	0.05(0.02 - 0.82)
KDD2015	0.09(0.02 - 0.74)	0.36(0.32 - 0.43)	$\overline{0.87(0.82 - 0.92)}$	0.14(0.03 - 0.53)	$\overline{0.57(0.52 - 0.64)}$	1.07(1.02 - 1.13)
Libimseti	0.37 (0.13  3.12)	0.70(0.59 - 0.97)	$\overline{1.17(1.09 - 1.38)}$	0.84(0.19 - 3.48)	$\overline{0.71(0.58 - 0.97)}$	$\overline{1.18(1.09 - 1.39)}$
$Movielens_1m$	0.34(0.06 - 2.92)	$\overline{0.56(0.35 - 0.99)}$	$\overline{1.06(0.30 - 1.39)}$	0.35(0.06 - 1.59)	0.72(0.51 - 1.24)	2.49(2.21 - 3.33)
TaFeng	0.05(0.02 - 0.19)	$\overline{0.53(0.43 - 0.63)}$	$\overline{1.99(1.68 - 2.27)}$	0.03(0.02 - 0.39)	0.55(0.47 - 0.68)	1.45(1.26 - 1.63)
$Movielens_100k$	0.07(0.02 - 0.32)	$\overline{0.35(0.31 - 0.57)}$	$\overline{0.87(0.83 - 1.04)}$	0.14(0.07 - 0.70)	$\overline{0.42(0.34 - 0.66)}$	$\overline{0.93(0.88 - 1.13)}$
YahooMovies	0.07(0.02 - 0.19)	$\overline{0.27(0.26 - 0.31)}$	$\overline{0.80(0.77 - 0.83)}$	0.09(0.04 - 0.30)	0.63(0.62 - 0.67)	$\overline{1.11(1.08 - 1.16)}$
20news	0.19(0.05-1.43)	2.95(1.88 - 3.96)	3.36(2.49 - 4.16)	0.10(0.03 - 0.76)	$\overline{1.94(1.34 - 2.69)}$	2.39(1.88 - 2.95)
Airline	0.02(0.01 - 0.04)	0.79(0.62 - 0.91)	$\overline{0.08(0.02 - 0.59)}$	0.02(0.02 - 0.03)	$\overline{1.18(0.96 - 1.33)}$	$\overline{0.10(0.02 - 0.79)}$
Twitter	0.03(0.01 - 0.05)	1.21(1.09 - 1.32)	0.37(0.09 - 1.09)	0.01(0.01 - 0.01)	0.89(0.82 - 0.95)	0.13(0.03 - 0.43)
# wins	13	0	0	13	0	0

Table 5: Median and interquantile range of computation time in seconds. For stochastic LIME/SHAP, this is the average median/range over 5 runs. The best (median) computation times are indicated in bold. The values are underlined if a method is **significantly worse than** the best method on a 1% significance level using a McNemar mid-p test [17].

		Linear		Nonlinear			
Dataset	EDC	LIME	SHAP	EDC	LIME	SHAP	
Ecommerce	0.00(0.00 - 0.01)	0.22(0.19 - 0.24)	0.00(0.00 - 0.01)	0.00(0.00 - 0.02)	0.27(0.26 - 0.28)	0.01(0.01 - 0.01)	
Facebook	0.11(0.02 - 1.19)	$\overline{0.35(0.28 - 0.51)}$	0.90(0.84 - 1.03)	0.17(0.02 - 2.03)	$\overline{0.39(0.32 - 0.55)}$	$\overline{0.95(0.88 - 1.07)}$	
Flickr	0.00(0.00 - 0.00)	$\overline{0.19(0.19 - 0.23)}$	$\overline{0.01(0.00-0.01)}$	0.00(0.00 - 0.02)	0.24(0.23 - 0.25)	$\overline{0.01(0.01 - 0.08)}$	
Fraud	0.00(0.00 - 0.02)	$\overline{0.24(0.22-0.28)}$	$\overline{0.02(0.01-0.17)}$	0.02(0.02 - 0.02)	0.65(0.60 - 0.72)	0.05(0.02 - 0.82)	
KDD2015	0.09(0.02 - 0.74)	$\overline{0.36(0.32 - 0.43)}$	$\overline{0.87(0.82 - 0.92)}$	0.14(0.03 - 0.53)	$\overline{0.57(0.52 - 0.64)}$	$\overline{1.07(1.02 - 1.13)}$	
Libimseti	0.37 (0.13 - 3.12)	0.70(0.59 - 0.97)	$\overline{1.17(1.09 - 1.38)}$	0.84(0.19 - 3.48)	$\overline{0.71(0.58 - 0.97)}$	1.18(1.09 - 1.39)	
$Movielens_1m$	0.34(0.06 - 2.92)	$\overline{0.56(0.35 - 0.99)}$	$\overline{1.06(0.30 - 1.39)}$	0.35(0.06-1.59)	0.72(0.51 - 1.24)	2.49(2.21 - 3.33)	
TaFeng	0.05(0.02 - 0.19)	$\overline{0.53(0.43 - 0.63)}$	$\overline{1.99(1.68 - 2.27)}$	0.03(0.02 - 0.39)	0.55(0.47 - 0.68)	$\overline{1.45(1.26-1.63)}$	
$Movielens_100k$	0.07(0.02 - 0.32)	$\overline{0.35(0.31 - 0.57)}$	$\overline{0.87(0.83 - 1.04)}$	0.14(0.07 - 0.70)	$\overline{0.42(0.34 - 0.66)}$	$\overline{0.93(0.88 - 1.13)}$	
YahooMovies	0.07(0.02 - 0.19)	$\overline{0.27(0.26 - 0.31)}$	$\overline{0.80(0.77 - 0.83)}$	0.09(0.04 - 0.30)	0.63(0.62 - 0.67)	$\overline{1.11(1.08 - 1.16)}$	
20news	0.19(0.05-1.43)	2.95(1.88 - 3.96)	3.36(2.49 - 4.16)	0.10(0.03 - 0.76)	$\overline{1.94(1.34 - 2.69)}$	2.39(1.88 - 2.95)	
Airline	0.02(0.01 - 0.04)	$\overline{0.79(0.62 - 0.91)}$	$\overline{0.08(0.02 - 0.59)}$	0.02(0.02 - 0.03)	$\overline{1.18(0.96-1.33)}$	$\overline{0.10(0.02 - 0.79)}$	
Twitter	0.03(0.01 - 0.05)	1.21(1.09 - 1.32)	0.37(0.09 - 1.09)	0.01(0.01-0.01)	0.89(0.82 - 0.95)	0.13(0.03 - 0.43)	
# wins	13	0	0	13	0	0	

Fig. 3: Computation time vs switching point for Facebook/linear



## 6. Discussion

#### Ability to rank positive evidence → Switching point

- EDC provides optimal (smallest) switching points for linear models
- Heuristic best-first algoritm EDC: worse than LIME/SHAP for some non-linear models

#### Percentage output generated

- When restricting the output size ( $\leq$  30), EDC *not always* generates output
- SHAP difficulties with Fraud data

#### **Explanation output size**

- EDC provides *smallest* output sizes
- LIME can be further reduced if wanted
- SHAP cannot be explicitly restricted (≥ 50% of active features included)

#### **Computational efficiency**

- Instances that are small and/or "easy" to explain with counterfactuals
- → EDC is most efficient
- LIME and SHAP *relatively fast* for all scenarios

## 7. Conclusion

## Comparative study of instance-level explanations EDC, LIME and SHAP for textual and behavioral data

- $\Rightarrow$  A **nuanced** conclusion:
- **EDC** seems best for *small* instances and *linear* models
- SHAP
  - Consistently relatively fast
  - Low switching points
  - Seems to have difficulties with highly-imbalanced data
  - Very large outputs
- LIME: best trade-off
  - Consistently relatively fast
  - Low switching points
  - Ability to provide k

#### 8. FURTHER RESEARCH

- 1. Extension of quantitative evaluation
- More data and models
- 2. Application (eg marketing, fraud detection)
- Specific business needs / domain experts
- Visualization of explanations
- Meta-features ⇔ fine-grained features
- 3. Qualitative evaluation of explanations
- Relevance of negative evidence?
- Counterfactual versus sparse, linear model?

# Thanks for your attention. Questions?

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