DaSSWeb
Data Science and Statistics Webinar

3rd December 2024

Designing Incentives for Collaborative Forecasting

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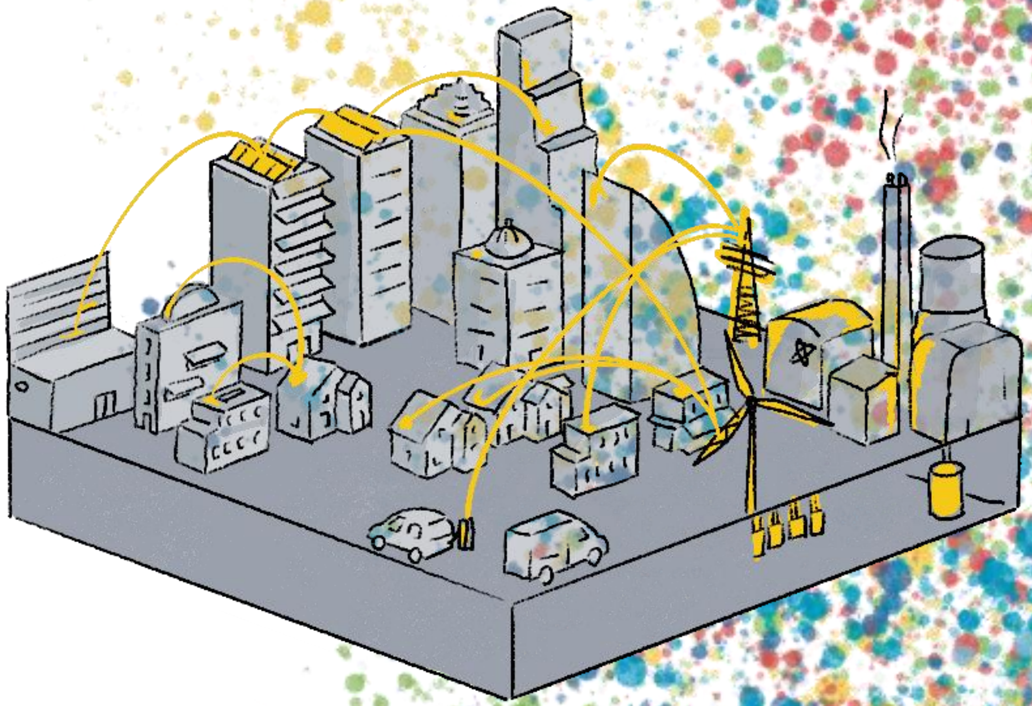
INESCTEC
INSTITUTE FOR SYSTEMS
AND COMPUTER ENGINEERING,
TECHNOLOGY AND SCIENCE

Context

Data Generation & Collection

Including in power systems …



Different types of data:

- Meteorological
- Network assets
- Generators
- Consumers
- …

Context

Data Generation & Collection

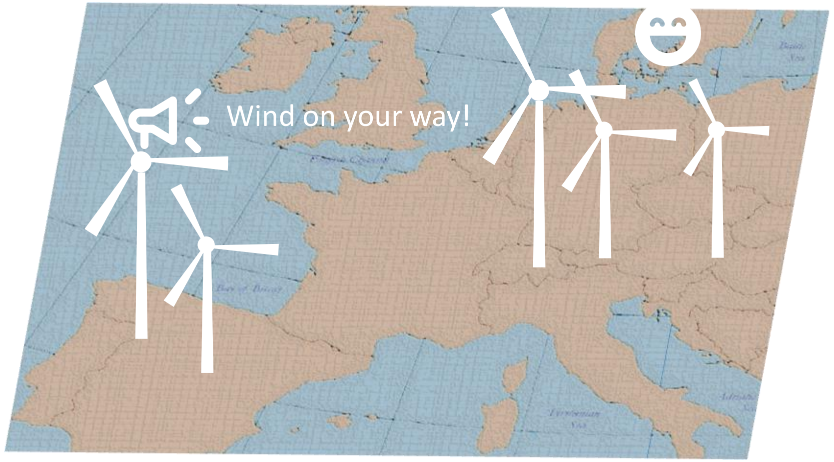
Collaborative Analytics

Combining data from multiple sources can increase the accuracy of forecasts

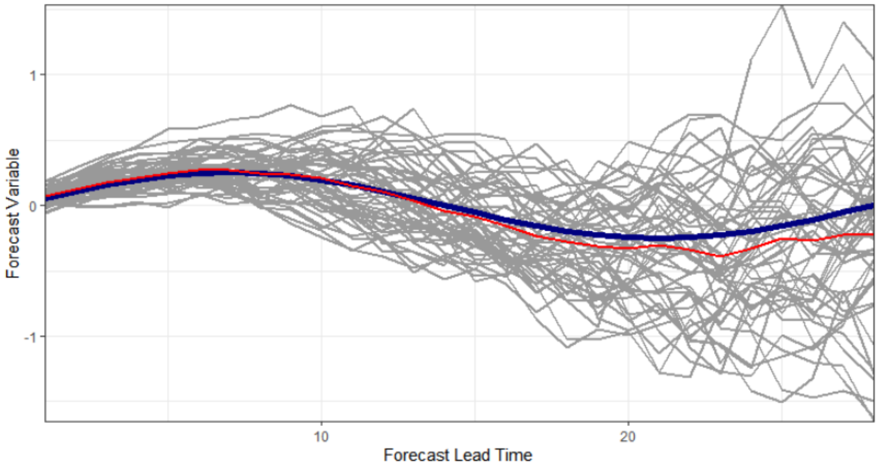
Open data sources

Proprietary data
(privacy, intellectual property, or regulatory reasons)

Spatio-temporal data
(helps models to capture e.g. weather patterns)

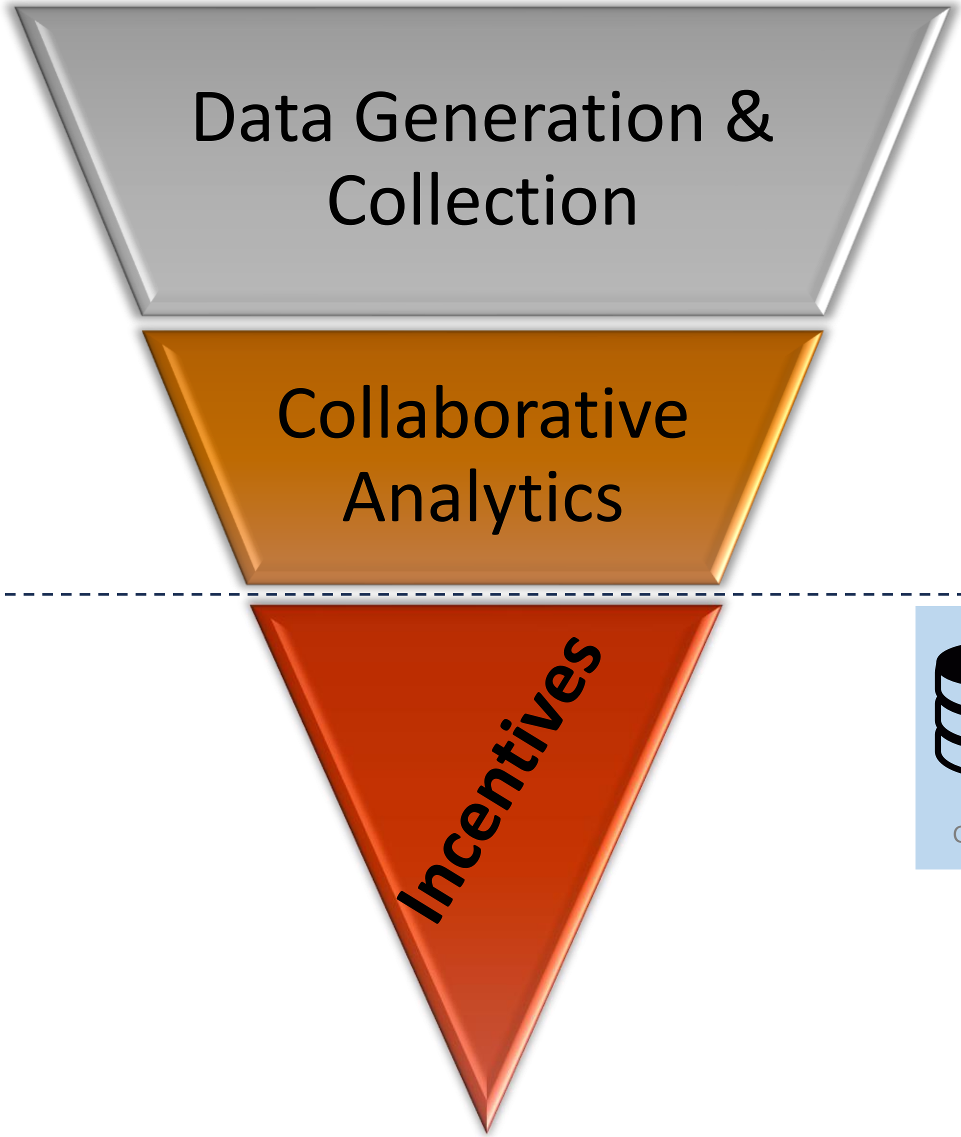


Multiple forecasts
(forecast ensemble are more stable)



Tastu et al. "Probabilistic forecasts of wind power generation accounting for geographically dispersed information." *IEEE Transactions on Smart Grid* 5.1 (2013): 480-489.

Context



Proprietary data
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Data privacy: collaborative analytics is performed without compromising data privacy

C. Gonçalves, R. J. Bessa, and P. Pinson. "Privacy-preserving distributed learning for renewable energy forecasting." *IEEE TSTE* 2021.

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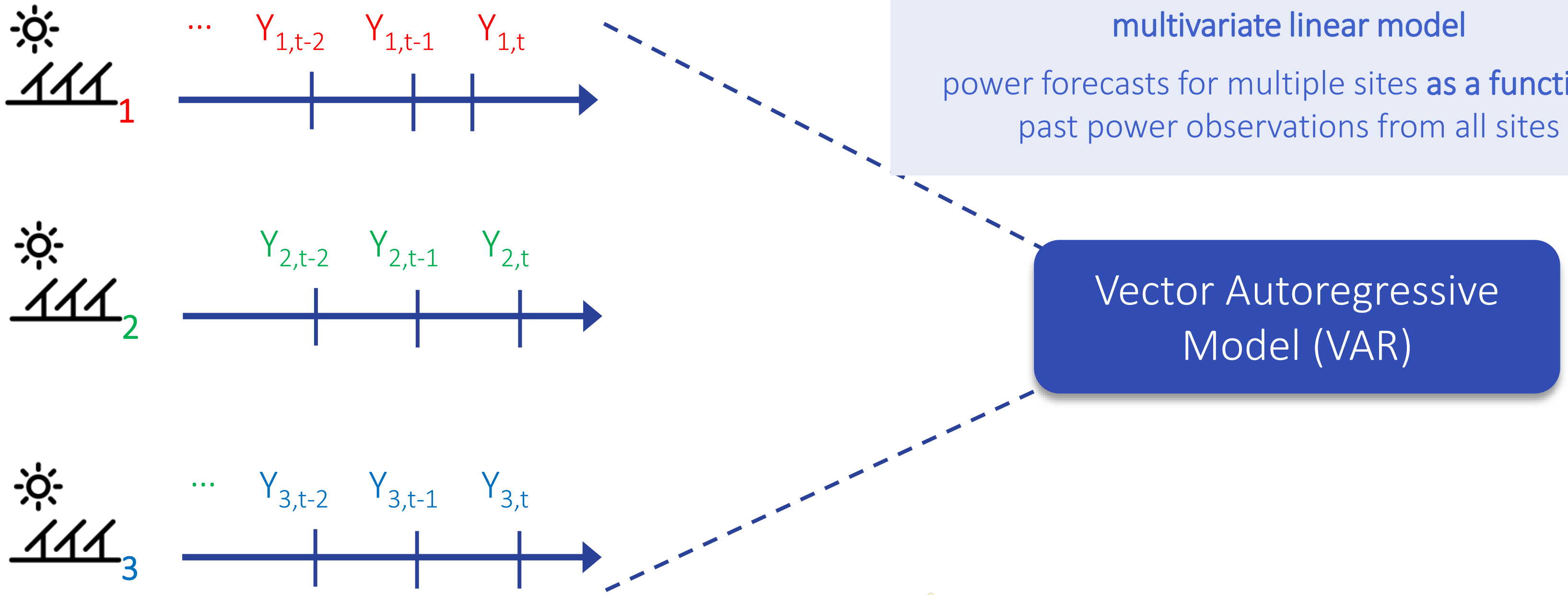
multivariate linear model

power forecasts for multiple sites **as a function of** past power observations from all sites



Example: 3 PV sites, 1 lag

These connections are a problem!

$$Y_{1,t} = c_1 + B^1_{1,1} Y_{1,t-1} + \boxed{B^1_{2,1} Y_{2,t-1} + B^1_{3,1} Y_{3,t-1}} + E_{1,t}$$

$$Y_{2,t} = c_2 + \boxed{B^1_{1,2} Y_{1,t-1}} + B^1_{2,2} Y_{2,t-1} + \boxed{B^1_{3,2} Y_{3,t-1}} + E_{2,t}$$

$$Y_{3,t} = c_1 + \boxed{B^1_{1,3} Y_{1,t-1} + B^1_{2,3} Y_{2,t-1}} + B^1_{3,3} Y_{3,t-1} + E_{3,t}$$

When compared against AR, VAR has reduced the average error by ~10% (h=1)

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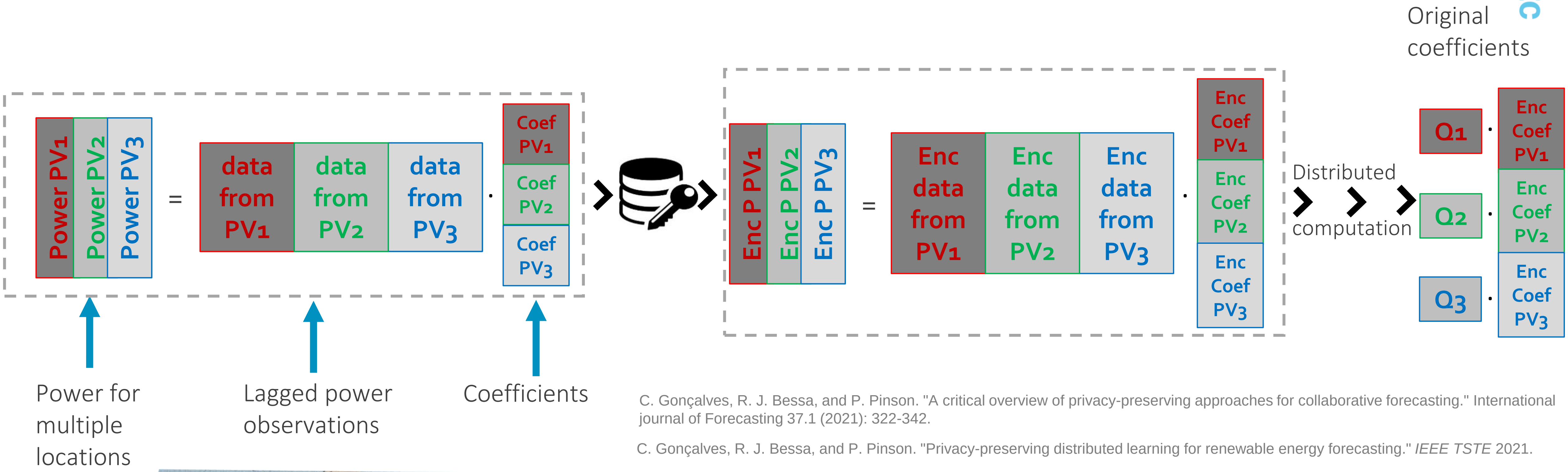
VAR MODEL



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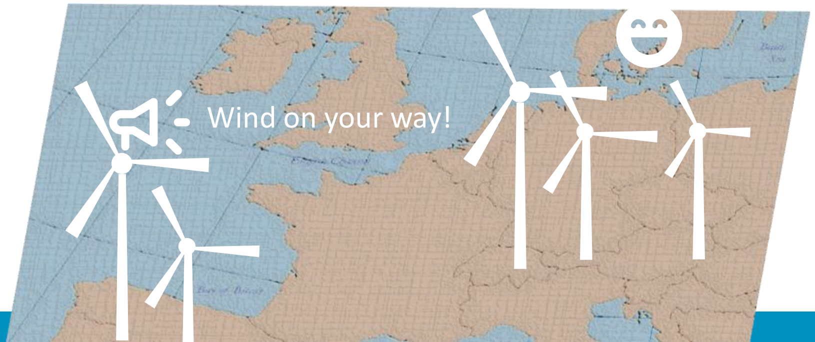

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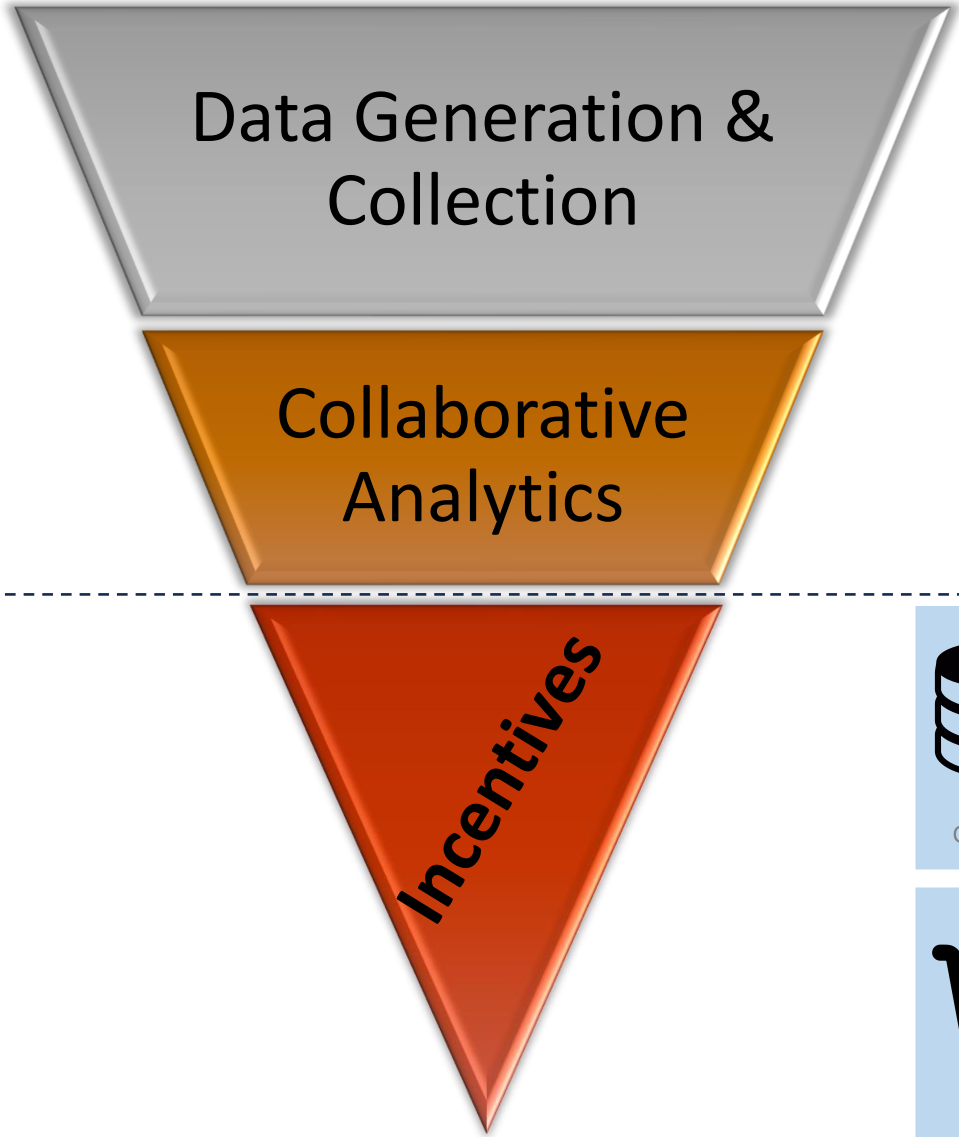

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Data markets: data privacy is a mandatory requirement but may not be enough

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Data owners want to improve their forecasts… or share data receive some compensation

data monetization

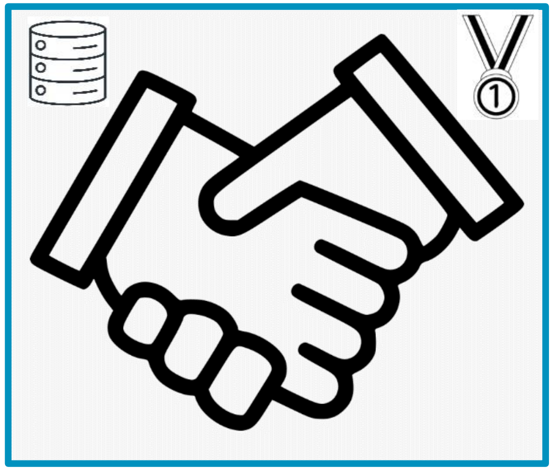
- ✓ **Data buyers: pay per accurate forecasts** with collaborative forecasting models
- ✓ **Data sellers: receive monetary compensation** proportional to the data importance when forecasting the others' data

barter trading (data by data)

- ✓ Data owners **provide and receive data** with approximately **the same value**
- ✓ **Value** is measured with metrics such as mutual information, correlation, etc.

data by service/recognition

- ✓ **Recognition** ,e.g., as a climate change mitigator
- ✓ Proportional to the data importance when forecasting the others' data



Simplest bidding strategy

Y, X4, P

I am willing to pay up to “P” for a prediction better than mine

Y = Const. + capturing nonlinearities

$$f1\_1(X1)*B1\_1 + \dots + f1\_M(X1)*B1\_M +$$
$$f2\_1(X2)*B2\_1 + \dots + f2\_M(X2)*B2\_M$$
$$f3\_1(X3)*B3\_1 + \dots + f3\_M(X3)*B3\_M$$
$$f4\_1(X4)*B4\_1 + \dots + f4\_M(X4)*B4\_M$$

subject to

$$p1*(1-I(B1\_1)*\dots*I(B1\_M)) +$$
$$p2*(1-I(B2\_1)*\dots*I(B2\_M)) +$$
$$p3\underbrace{*(1-I(B3\_1)*\dots*I(B3\_M)) \leq P}_{\text{check if at least one variable related to X3 is used}}$$

If my variable “X1” is used to generate forecasts, I want to receive “p1”

X1, p1

X2, p2

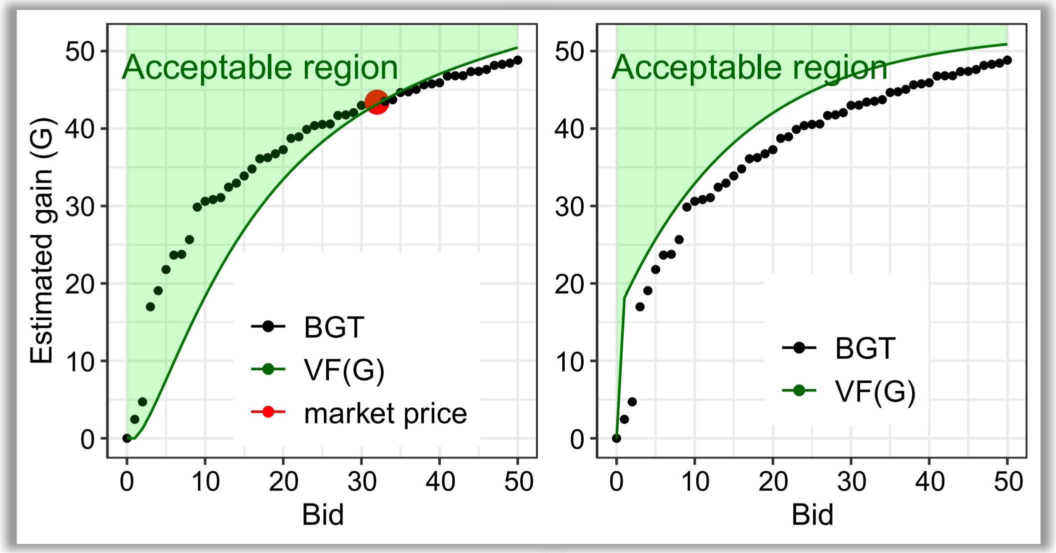
X3, p3

G. Yu, H. Fu, and Y. Liu. "High-dimensional cost-constrained regression via nonconvex optimization.“ *Technometrics* 64.1 (2022): 52-64.

Buyer bids based on accuracy improvement

I am willing to pay according to my accuracy improvement

Y, X4, P(gain)



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X1, p1

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C. Gonçalves, R. J. Bessa, T. Teixeira, J. Vinagre. "Budget-constrained Collaborative Renewable Energy Forecasting Market." under review IEEE TSTE (3rd round)

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INESCTEC

Case Study | Synthetic datasets

Y = f(X3, X7, X12, X21, X31, X48, X51, X63, X37, X90)

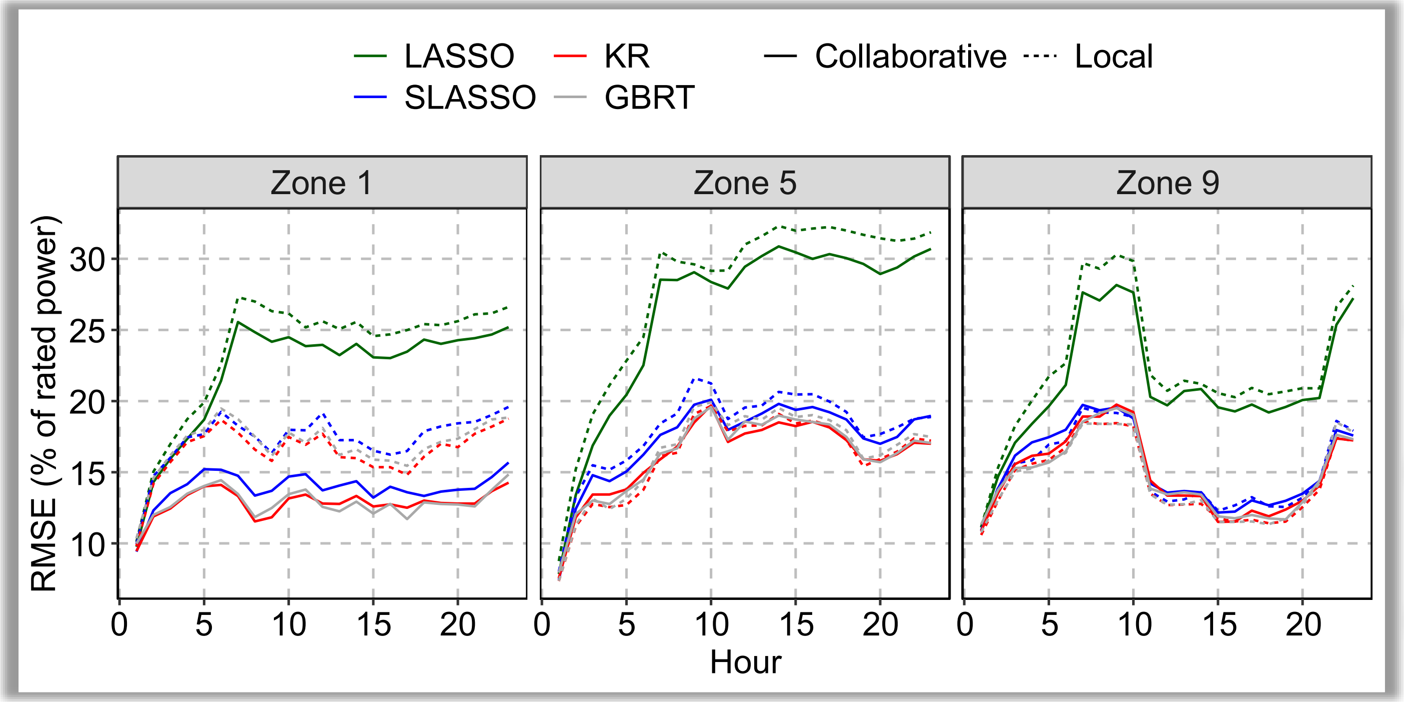
- **Data buyer** with **one target** and **ten covariates** (X1, X2, …, X10)
- **90 features available** on data market (X11, …, X100)
- X37 costs 11 cents, all the others cost 10
- X3 similar to X73 (will the market select X73?)
- X37 similar to X74 (will the market select the cheapest option?)

TABLE I: Data allocation and relevance (synthetic datasets).

Linear			**Non-linear**		
Optimal	**Case #1**	**Case #2**	**Optimal**	**Case #1**	**Case #2**
21 (22.73)	21 (26.33)	21 (22.86)	21 (15.45)	21 (28.50)	21 (25.30)
90 (20.45)	90 (23.88)	90 (20.69)	90 (14.70)	90 (22.60)	90 (20.01)
63 (18.18)	63 (20.86)	63 (18.07)	63 (13.98)	63 (20.52)	63 (17.92)
48 (15.91)	48 (18.25)	48 (15.81)	48 (13.30)	48 (18.67)	48 (17.18)
37 (9.09)	74 (10.68)	74 (8.95)	37 (11.45)	74 (9.72)	74 (8.39)
51 (6.81)	–	51 (6.78)	51 (10.89)	–	51 (7.32)
12 (4.55)	–	12 (4.51)	12 (10.36)	–	12 (3.88)
31 (2.27)	–	31 (2.33)	31 (9.85)	–	–
others (0)	–	–	others (0)	–	–

Case Study | Global Energy Forecasting Competition 2014 (GEFCom2014)

- **Normalized hourly wind power** measurements for 10 zones
- 24-hour-ahead **forecasts for zonal and meridional wind components** at 10m and 100m above ground level, issued daily at 00h00 to production locations.



Train + forecast times:

- KR 801 seconds
- GBRT 414 seconds
- Spline LASSO 93 seconds

! collaborative models outperfom local models

! improvement significantly varies between zones

! these are mean values for the year 2013!

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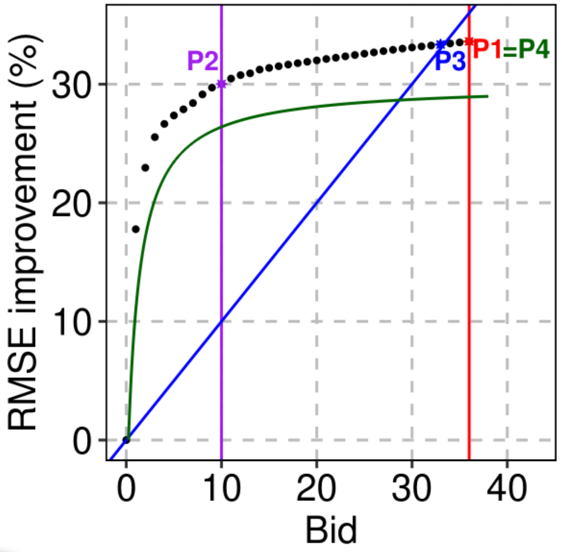
- 24-hour-ahead **forecasts for zonal and meridional wind components** at 10m and 100m above ground level, issued daily at 00h00 to production locations.

! Higher buyer budgets lead to better performance

! Data owners improve accuracy and/or receive monetary compensations



! Sellers' bid are 1 per X

	SLCM											
	Payment (↑)				Revenue (↓)				Mean gain ($\mathcal{G}$(%))			
i	$\mathcal{VF}^1$	$\mathcal{VF}^2$	$\mathcal{VF}^3$	$\mathcal{VF}^4$	$\mathcal{VF}^1$	$\mathcal{VF}^2$	$\mathcal{VF}^3$	$\mathcal{VF}^4$	$\mathcal{VF}^1$	$\mathcal{VF}^2$	$\mathcal{VF}^3$	$\mathcal{VF}^4$
1	157941	22613	137907	60296	103211	17487	97387	44119	25.12	24.73	24.97	29.17
2	142742	29807	132772	59504	108121	22791	102774	47721	15.42	16.44	15.49	20.61
3	93827	14841	95458	33192	113268	21878	106349	48788	-1.87	-3.83	-1.86	-0.12
4	102468	22132	88939	47110	107611	10002	102073	43326	20.42	21.17	20.41	27.66
5	90894	14798	75095	44988	111547	18793	106193	46274	25.10	25.80	25.10	35.91
6	109366	18966	110560	42373	107990	18288	100552	44986	19.41	19.83	19.43	29.22
7	71848	12380	72478	38203	111038	21017	102800	44847	9.62	9.20	9.61	15.14
8	56730	10185	55863	36400	114681	28750	107278	47615	4.59	3.14	4.51	8.92
9	116838	25235	106607	48752	109046	19486	103044	46712	10.52	11.88	10.55	16.22
10	150819	32551	152278	52924	106960	25016	99507	46560	11.39	11.62	11.41	18.55

Next Generation Reservoir Computing

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[4]Clarkson Center for Complex Systems Science (C^3S^2), Potsdam, NY 13699, USA

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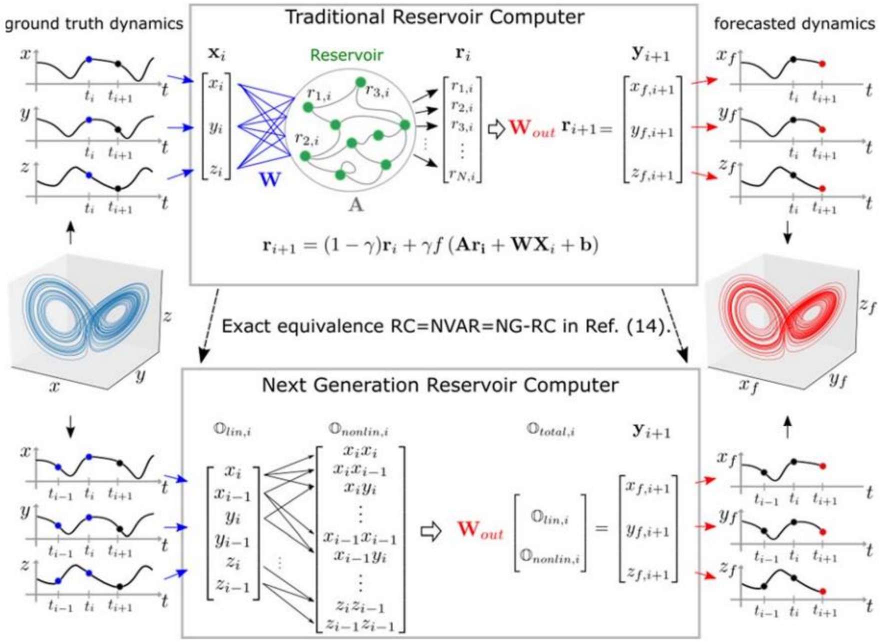
July 21, 2021



- **Mixed effects:** product between lags

"a linear combination of mixed effects among (shifted) time series can serve as a powerful model(…), effectively capturing dynamic system data through observed time series."

(quadratic knapsack problems if we consider two times)

- **Classification:** logistic regression

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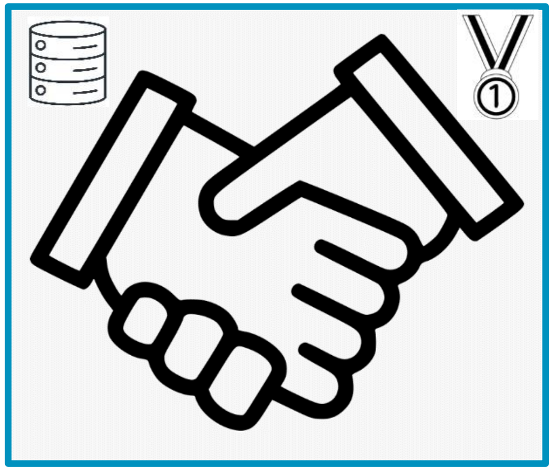


barter trading (data by data)

I am willing to share and receive data with similar value

Y4, X4_1, X4_2, X4_3

$$\arg\max_{z^j_{j'\to i}\in\{0,1\}} \underbrace{\sum_i \sum_{j\neq i} \sum_{j'\in\Omega_j} \mathrm{V}^j_{j'\to i} z^j_{j'\to i}}_{\text{total value exchange}}$$

subject to

$$\Big|\underbrace{\sum_{i'=1}^{n_i}\sum_j \mathrm{V}^i_{i'\to j} z^i_{i'\to j}}_{i\text{-th data owner shared value}} - \underbrace{\sum_k\sum_{k'=1}^{n_k} \mathrm{V}^k_{k'\to i} z^k_{k'\to i}}_{i\text{-th data owner received value}}\Big| \le \epsilon, \quad \forall i$$

$$\underbrace{\sum_{\{m',m\}\in\mathcal{C}_c} z^m_{m'\to i} \le 1, \forall i, c}_{\text{condition to capture redundancy}}$$

Linear Problem

$V^j_{j'\to i}$: value of Xj_j' when forecasting Y_i, conditional on Xi_1, Xi_2, Xi_3

maximize value allocation

subject to |shared-received value|<eps
no redundant data allocated

Y1, X1_1, X1_2, X1_3

Y2, X2_1, X2_2, X2_3

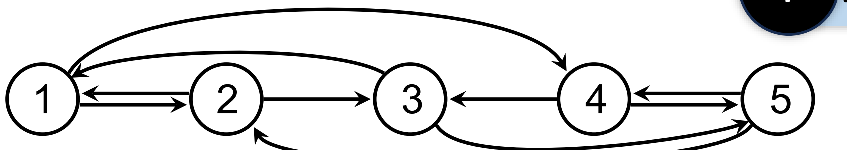
Y3, X3_1, X3_2, X3_3

barter trading (data by data)

Case Study | Synthetic datasets

… evaluating metrics

! Each agent has 30 covariates



$\Gamma_1 = \{2,3\}, \Gamma_2 = \{1,5\}, \Gamma_3 = \{2,4\}, \Gamma_4 = \{1,5\}, \Gamma_5 = \{3,4\}$

$$60X_i^3 + 40X_i^7 + \sum_{j\in\Gamma_i}\left[16.1X_j^{11} + 6.5X_j^{13} + 19.4X_j^{19} + 25.8X_j^{24} + 32.3X_j^{27}\right] + \varepsilon$$

	linear			exponential			quadratic (no interactions)		
	recall	precision	time (s)	recall	precision	time (s)	recall	precision	time (s)
Pearson	1.00(±0.00)	0.64(±0.06)	5.13	1.00(±0.00)	0.59(±0.09)	5.12	0.12(±0.14)	0.16(±0.18)	5.06
Spearman	1.00(±0.00)	0.63(±0.08)	16.59	1.00(±0.00)	0.64(±0.10)	16.19	0.07(±0.07)	0.15(±0.17)	16.54
Kendall	1.00(±0.00)	0.63(±0.08)	9.59	1.00(±0.00)	0.64(±0.09)	9.39	0.05(±0.08)	0.11(±0.17)	9.65
MI	0.95(±0.04)	0.69(±0.11)	3.29	0.80(±0.09)	0.69(±0.07)	3.48	0.98(±0.04)	0.64(±0.08)	3.54
ϕ_k	0.90(±0.07)	0.68(±0.08)	1665.08	0.58(±0.14)	0.48(±0.10)	1658.37	0.90(±0.04)	0.58(±0.05)	1667.59
dcor	1.00(±0.00)	0.65(±0.03)	64.95	1.00(±0.00)	0.65(±0.08)	64.02	0.98(±0.04)	0.66(±0.13)	65.24
Partial Pearson	1.00(±0.00)	0.57(±0.05)	83.49	1.00(±0.00)	0.58(±0.09)	83.64	0.07(±0.07)	0.13(±0.13)	83.18
Partial Spearman	1.00(±0.00)	0.58(±0.06)	422.48	1.00(±0.00)	0.60(±0.05)	422.05	0.03(±0.08)	0.07(±0.15)	421.78
CMI	0.90(±0.04)	0.81(±0.08)	35.96	0.75(±0.06)	0.96(±0.08)	39.36	0.98(±0.04)	0.66(±0.11)	37.60
MRMR Pearson	1.00(±0.00)	0.62(±0.07)	17.38	1.00(±0.00)	0.71(±0.18)	17.24	0.10(±0.11)	0.14(±0.16)	17.80
MRMR Spearman	1.00(±0.00)	0.60(±0.09)	141.44	1.00(±0.00)	0.65(±0.06)	141.35	0.05(±0.08)	0.10(±0.17)	141.66
MRMR Kendall	1.00(±0.00)	0.60(±0.09)	839.84	1.00(±0.00)	0.65(±0.06)	842.25	0.05(±0.08)	0.10(±0.17)	841.30
MRMR MI	1.00(±0.00)	0.69(±0.16)	104.99	0.80(±0.04)	0.66(±0.11)	105.72	1.00(±0.00)	0.65(±0.06)	105.55
MRMR ϕ_k	0.95(±0.04)	0.67(±0.15)	2550.40	0.48(±0.15)	0.50(±0.18)	2571.69	0.93(±0.07)	0.61(±0.05)	2562.87
MRMR dcor	1.00(±0.00)	0.58(±0.01)	1606.65	1.00(±0.00)	0.62(±0.11)	1601.20	0.98(±0.04)	0.67(±0.07)	1604.79
PermImp (GBR)	1.00(±0.00)	0.72(±0.04)	3288.71	0.90(±0.07)	1.00(±0.00)	1812.93	1.00(±0.00)	0.63(±0.12)	2122.35
Impurity (GBR)	0.83(±0.00)	1.00(±0.00)	1956.00	0.70(±0.04)	0.98(±0.05)	1149.63	0.83(±0.00)	1.00(±0.00)	1404.10
SHAP (GBR)	1.00(±0.00)	0.10(±0.00)	2020.25	1.00(±0.00)	0.12(±0.02)	1152.52	1.00(±0.00)	0.10(±0.00)	1409.82

Non-conditional

Conditional to owned data

! Permutation hypothesis test (if p-value <5% feature is relevant)

! Recall = TP / (TP + FN)

! Precision = TP / (TP + FP)

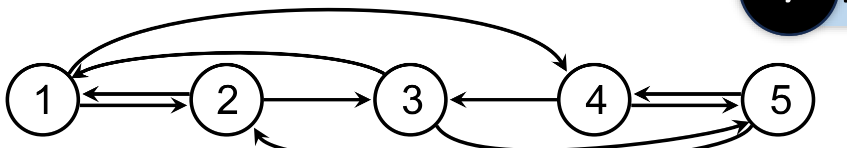
! MRMR MI has the best trade-off between the 3 criteria

barter trading (data by data)

Case Study | Synthetic datasets

… relation with data value?

! Each agent has 30 covariates



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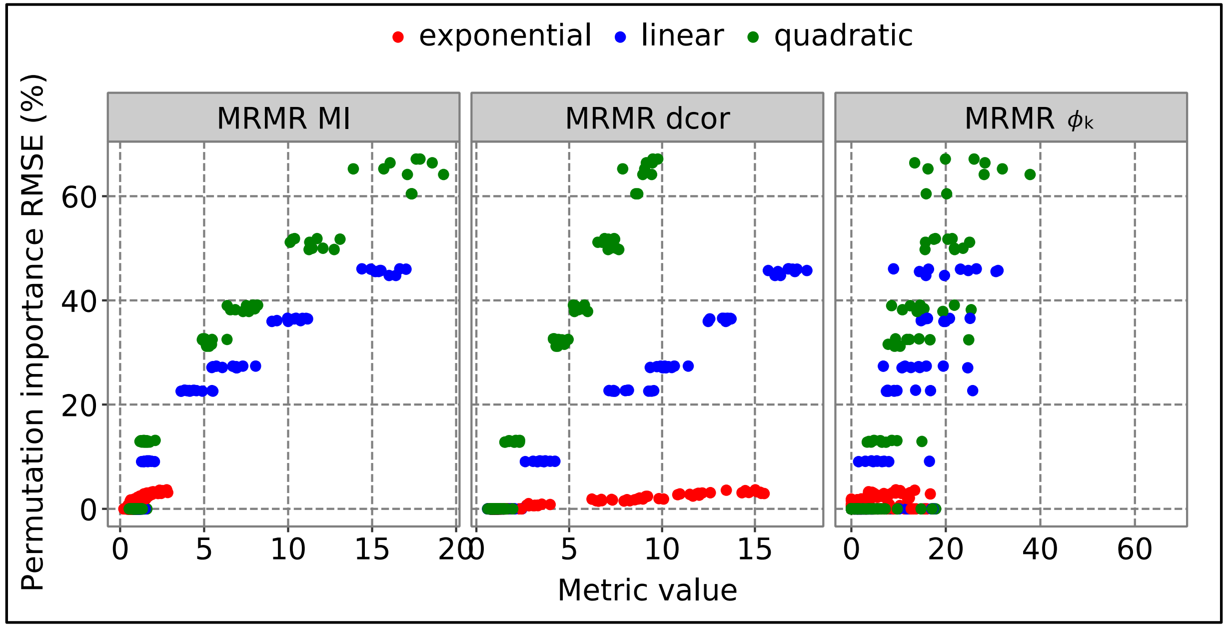


		Owner 1	Owner 2	Owner 3	Owner 4	Owner 5
Linear	Correctly exchanged	9	10	9	10	9
	Wrongly exchanged	2	4	3	2	8
Exponential	Correctly exchanged	8	6	9	7	6
	Wrongly exchanged	4	3	2	4	6
Quadratic	Correctly exchanged	10	10	9	7	10
	Wrongly exchanged	2	5	7	5	1

! MRMR MI has the best trade-off between the 3 criteria

Case Study | Global Energy Forecasting Competition 2014 (GEFCom2014)

RMSE for January 2013

Zone	Local	Proposal	Collaborative
1	19.72	14.58	13.15
2	27.57	26.53	25.97
3	34.37	35.06	34.96
4	27.15	27.09	27.00
5	31.26	31.06	31.07
6	32.38	32.46	31.44
7	14.22	14.11	14.4
8	14.49	14.66	14.77
9	20.37	19.94	20.03
10	43.48	42.92	42.09

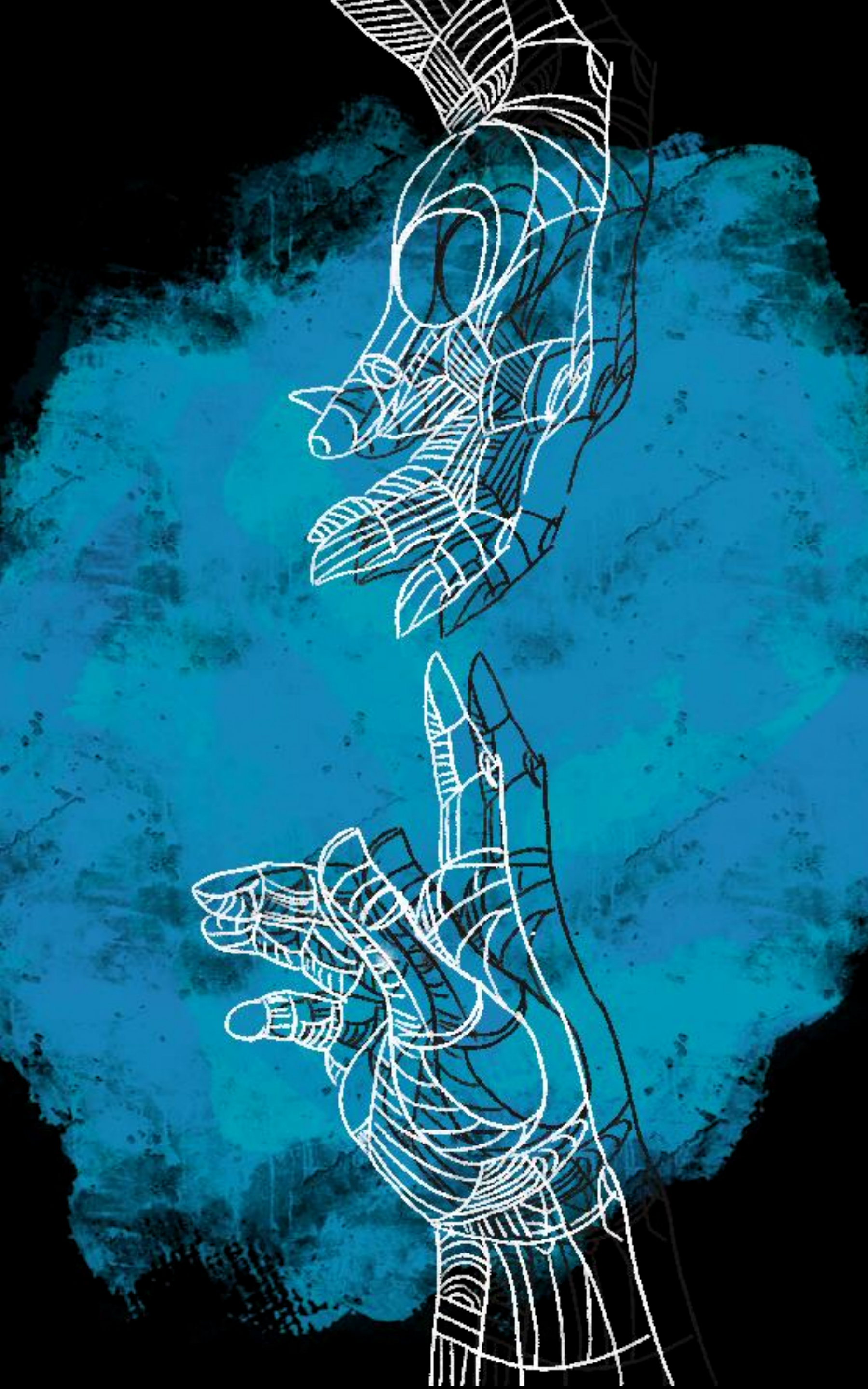
! Zone 1 has higher rmse improvement → shared information with all other zones!

! Zone 2 has the second higher rmse improvement and the second higher shared value

! Remaining zones shared lower value

Key messages

- **Collaborative forecasting** has potential to improve forecasting accuracy in many use cases
- **Data sharing incentives** are needed to promote such collaboration
- Incentives explored by our team:
    - Data monetization
    - Barter trading
- Projects



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Researcher
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Fernando Paula
Researcher
CPES @ INESC TEC

Thank you!

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