

OTIMIZANDO A DETECÇÃO DE CIBERATAQUES COM ENSEMBLE LEARNING

Thiago José Lucas, Ph.D.

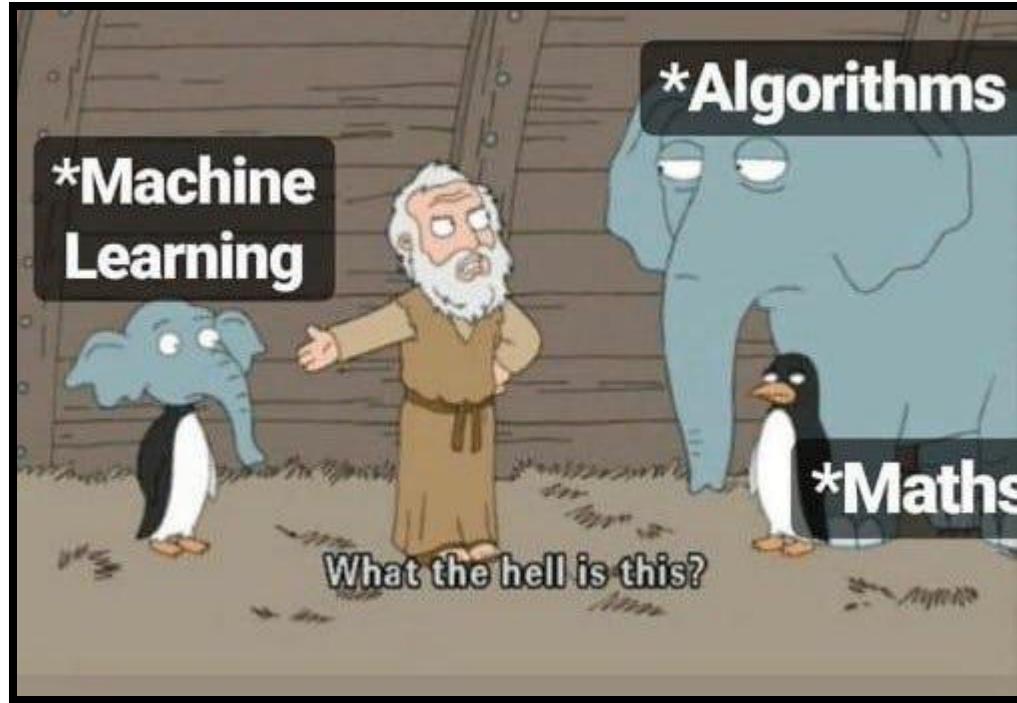


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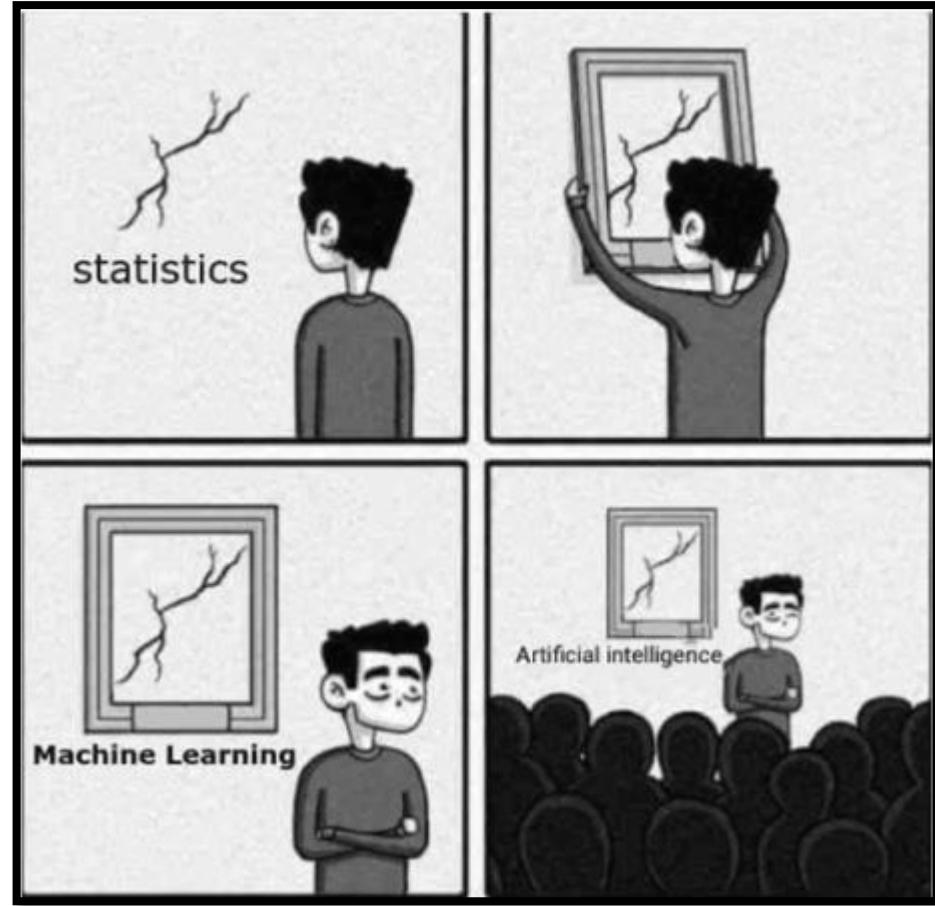
O QUE É “APRENDIZAGEM DE MÁQUINA”?



Aplicações tradicionais

- Classificação
- Regressão
- Clustering

O QUE É “APRENDIZAGEM DE MÁQUINA”?



Como a máquina aprende?

- Com supervisão
- Sem supervisão
- Semi-supervisão, reforço, etc

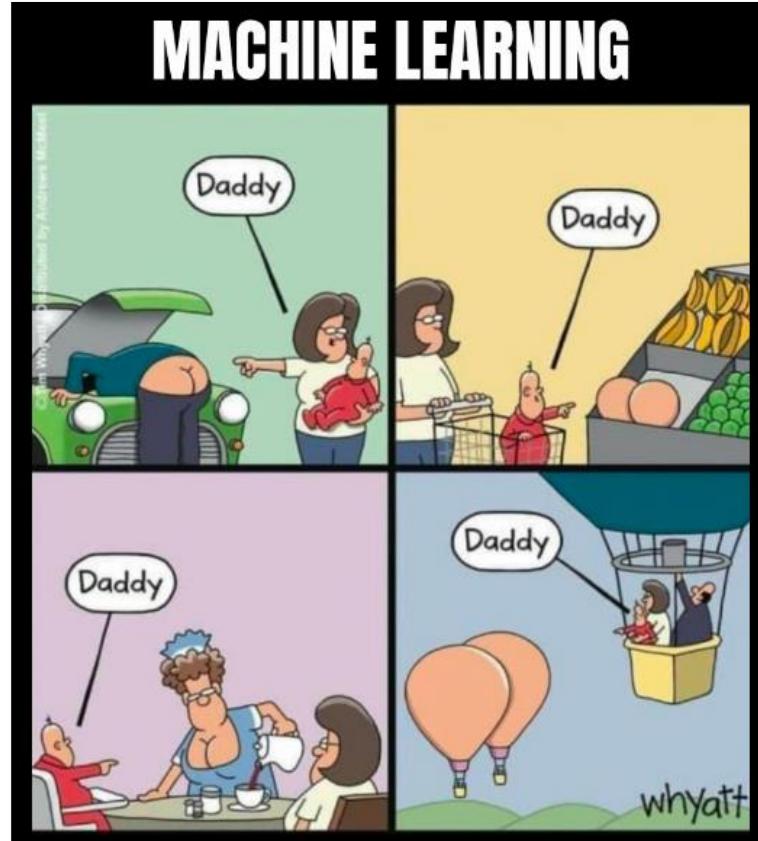
QUAL A IMPORTÂNCIA NO BLUE TEAM?



Evolução

- Mudança brusca do blue team raiz 😊
- A complexidade dos ataques recentes
- Seus mecanismos de defesa estão adaptados aos 0-days?
- O que não é benéfico, é malicioso!

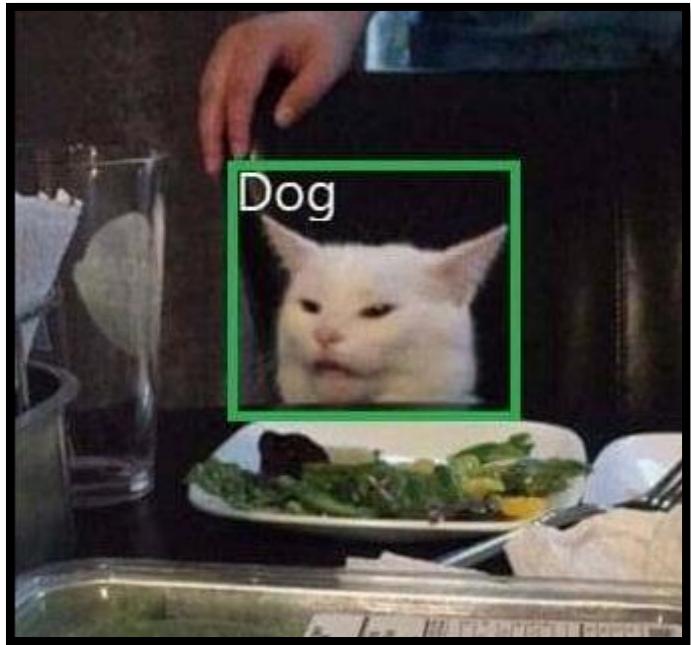
COMO USAR EM BENEFÍCIO DO BLUE TEAM?



Detecção de Intrusão

- Reconhecimento de ataques

COMO USAR EM BENEFÍCIO DO BLUE TEAM?

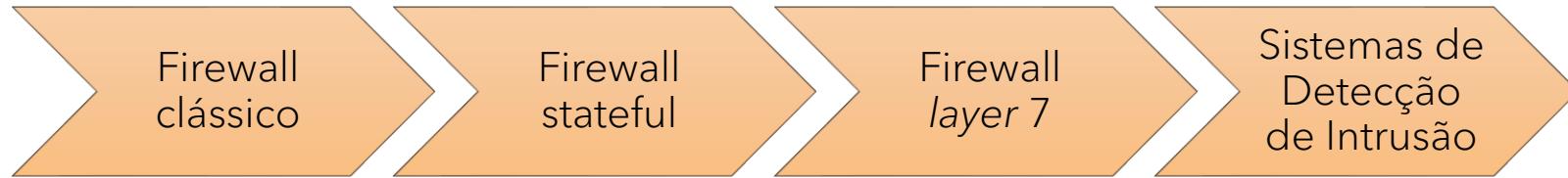


Redução dos erros de classificação

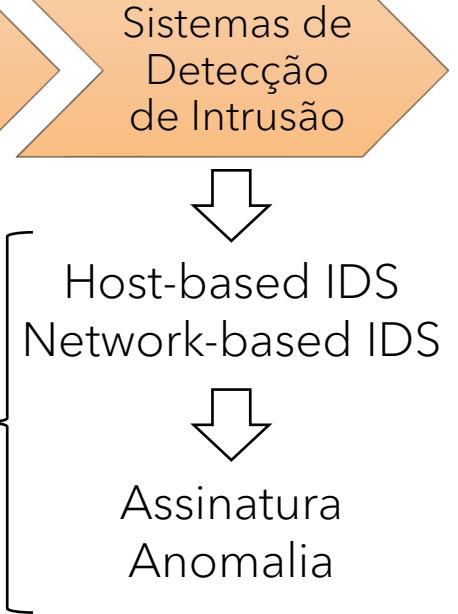
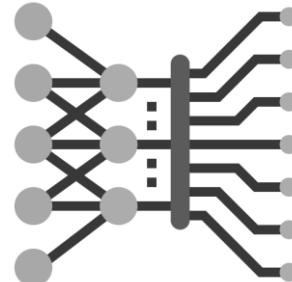
- IDSs tradicionais erram mais (muito mais!)
- É possível errar menos (quase nada)
 - Datasets confiáveis
 - Pré-processamento adequado
 - Algoritmos robustos e otimizados

COMO USAR EM BENEFÍCIO DO BLUE TEAM?

- Evolução
- Relação "IA/IDS"

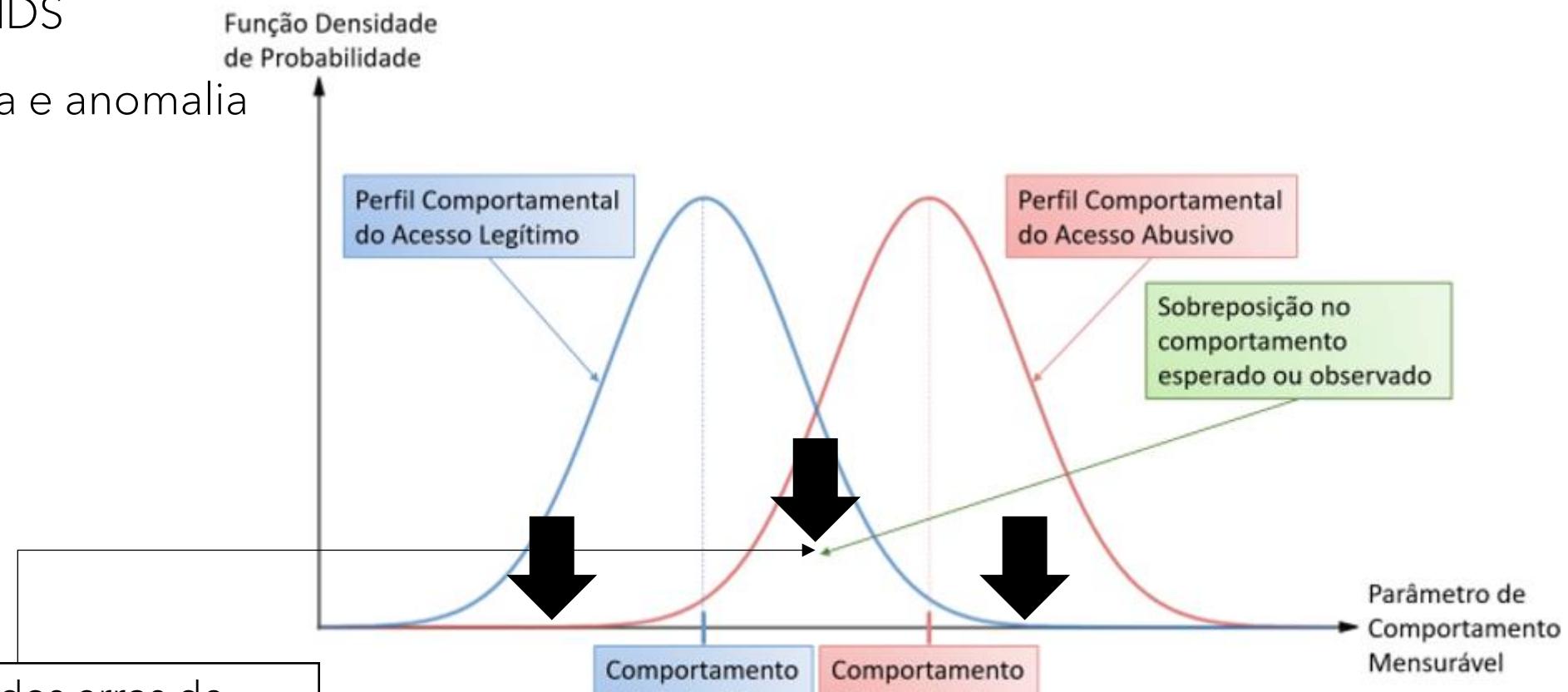


- Métodos matemático/estatísticos
 - Reconhecimento de padrões complexos
 - Modelos robustos



SISTEMAS DE DETEÇÃO DE INTRUSÃO

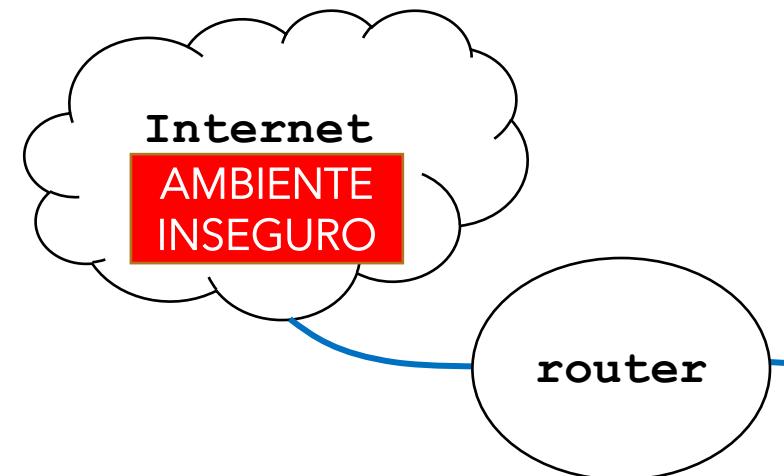
- HIDS e NIDS
- Assinatura e anomalia



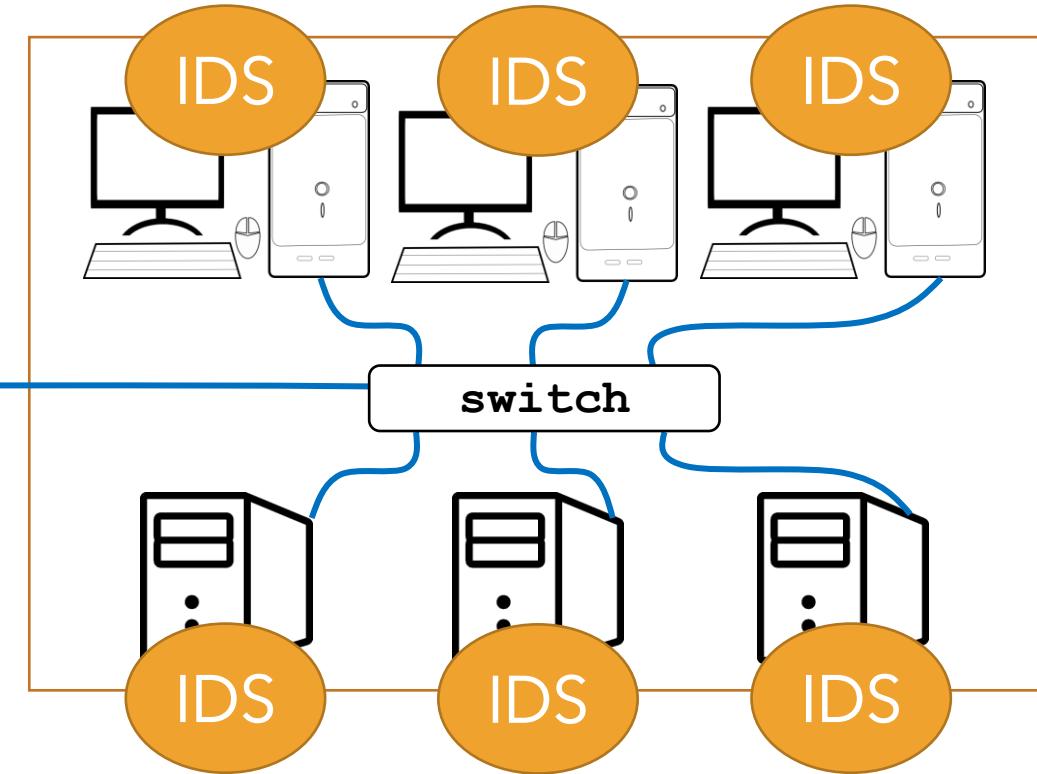
- Diminuição dos erros de classificação (FN / FP)
- Consequente incremento de acurácia / performance

SISTEMAS DE DETECÇÃO DE INTRUSÃO

- HIDS e NIDS
- Assinatura e anomalia



Host-based IDS

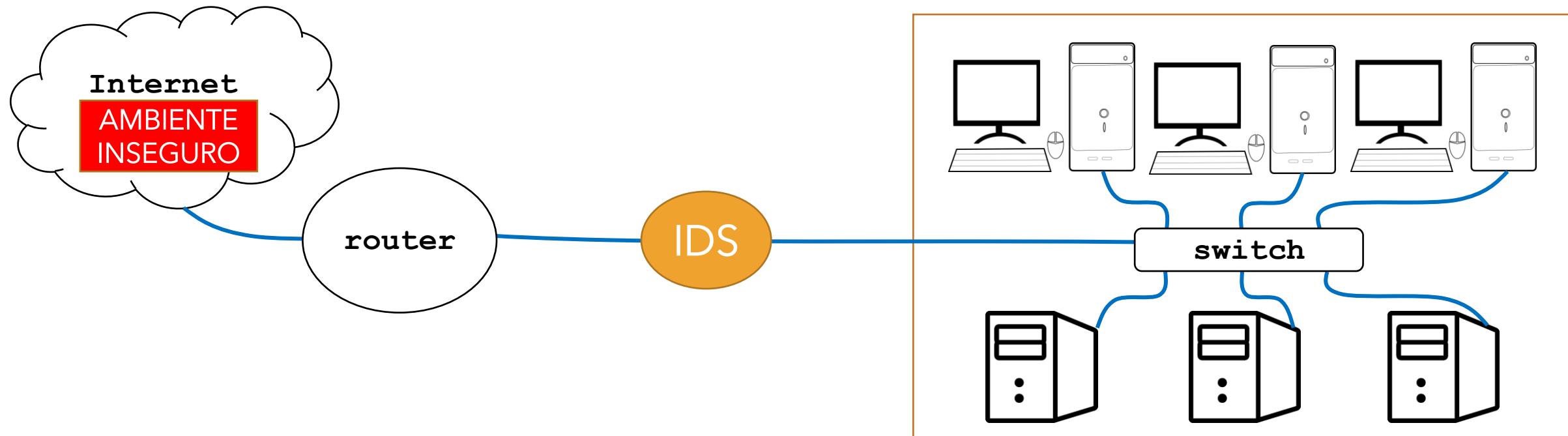


SISTEMAS DE DETEÇÃO DE INTRUSÃO

- HIDS e NIDS
- Assinatura e anomalia

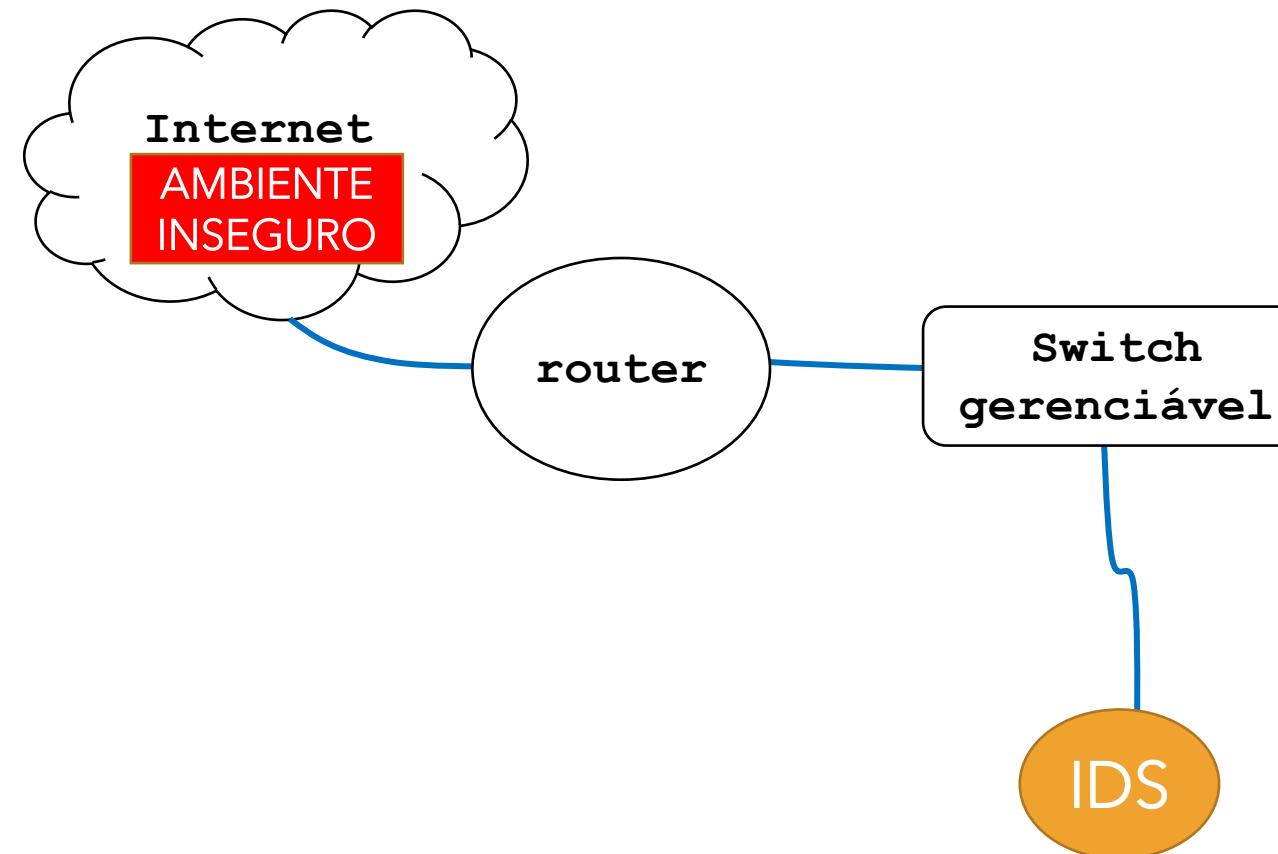
Network-based IDS

- Bridge
- Espelhamento



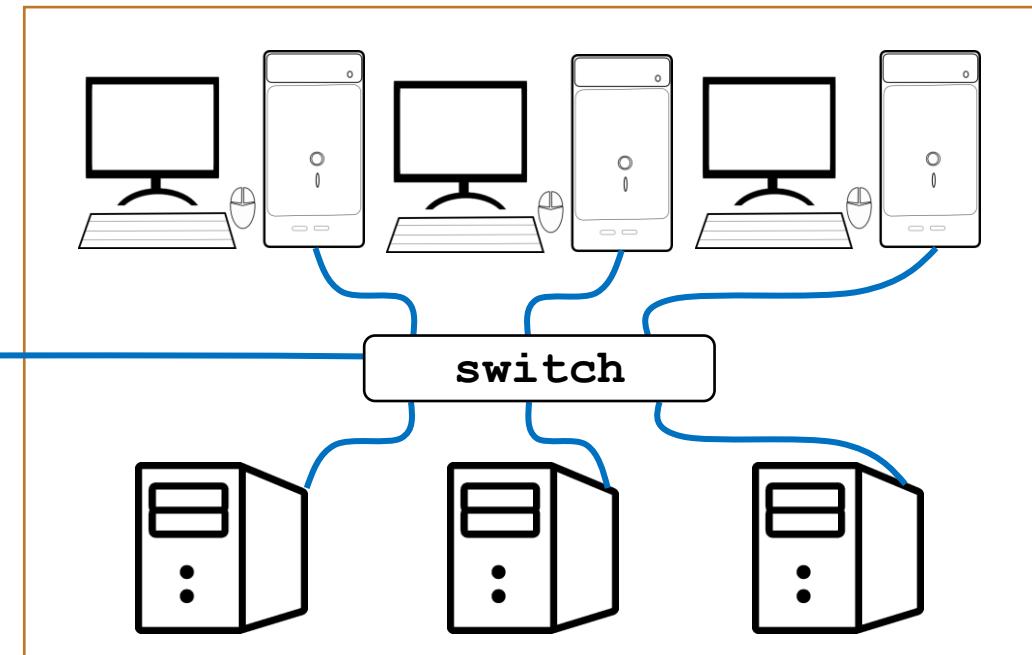
SISTEMAS DE DETECÇÃO DE INTRUSÃO

- HIDS e NIDS
- Assinatura e anomalia



Network-based IDS

- Bridge
- Espelhamento



E COMO SE FAZ ISSO?



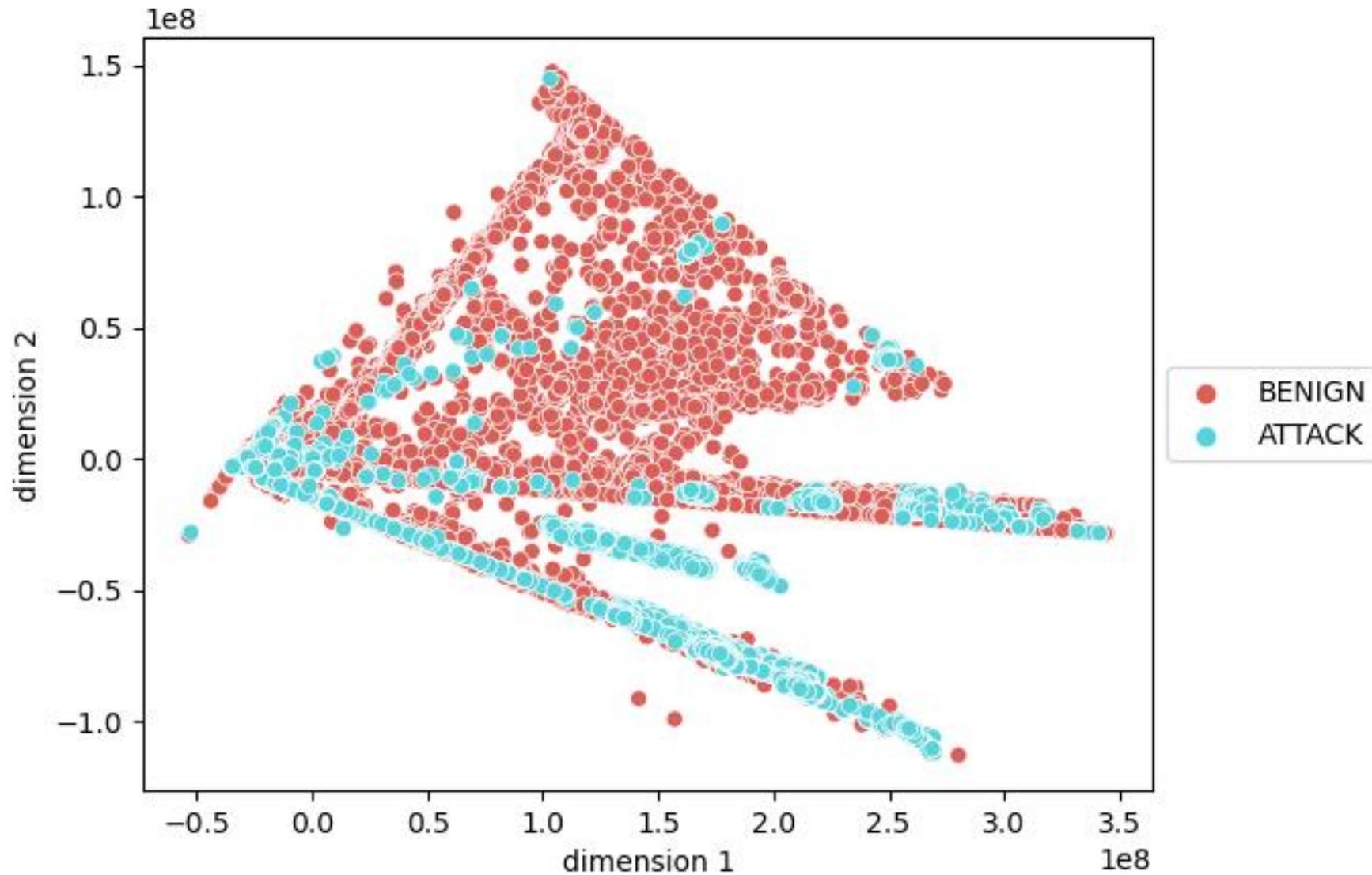
DATASET

Mostrar um dataset aleatório

DATASET

Category		Total	Total(-rows lack info)	with	Training	Test
BENIGN	BENIGN	2273097	2271320		20000	20000
DOS	DDoS	128027	128025		2700	3300
	DoS slowloris	5796	5796		1350	1650
	DoS Slowhttptest	5499	5499		2171	1169
	DoS Hulk	231073	230124		4500	5500
	DoS GoldenEye	10293	10293		1300	700
	Heartbleed	11	11		5	5
	PortScan	158930	158804		3808	4192
Bot	Bot	1966	1956		936	624
Brute-Force	FTP-Patator	7938	7935		900	1100
	SSH-Patator	5897	5897		900	1100
Web Attack	Web Attack-Brute Force	1507	1507		910	490
	Web Attack-XSS	652	652		480	160
	Web Attack-SQL Injection	21	21		16	4
Infiltration	Infiltration	36	36		24	6
Total Attack		471454	470365		20000	20000
Total		2830743	2827876		40000	40000

DATASET



TREINAMENTO

→ (x) src.port

TREINAMENTO

(y) dest.port



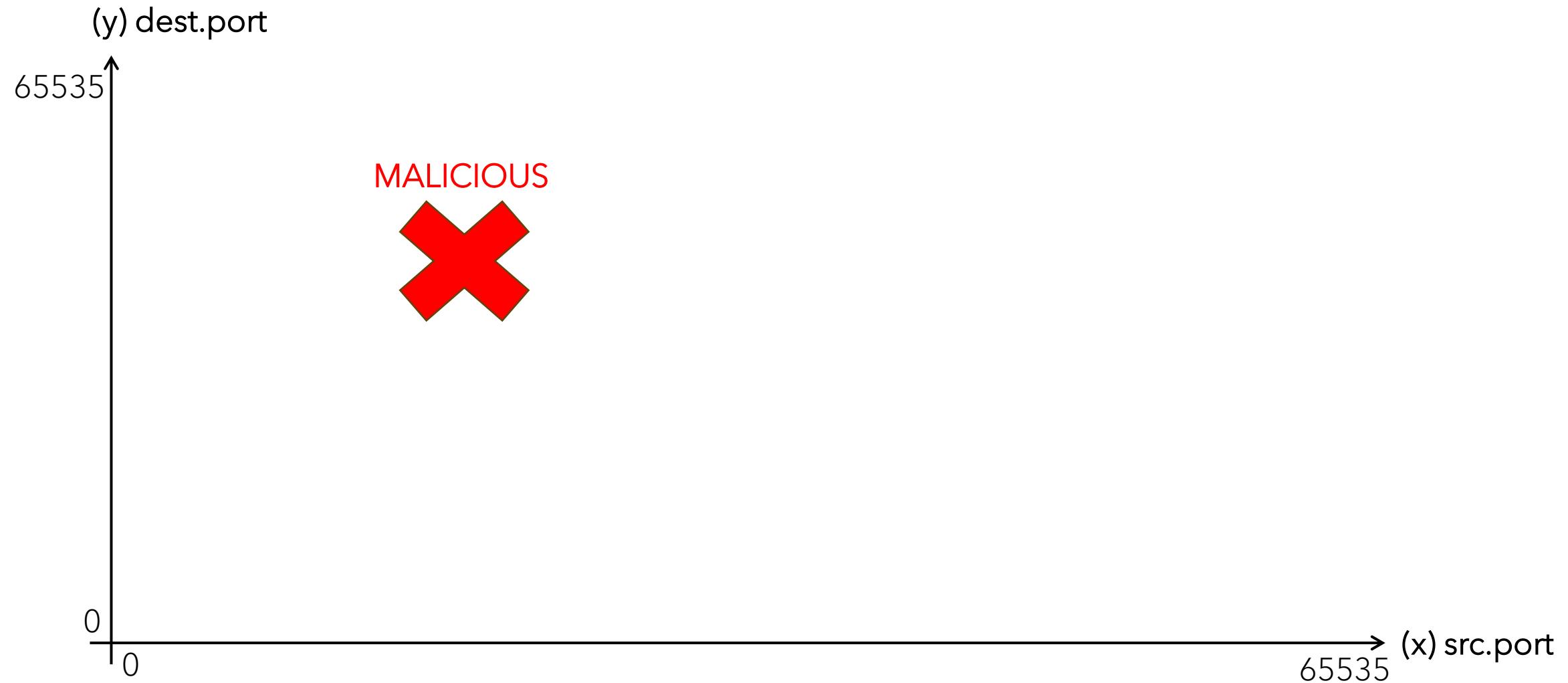
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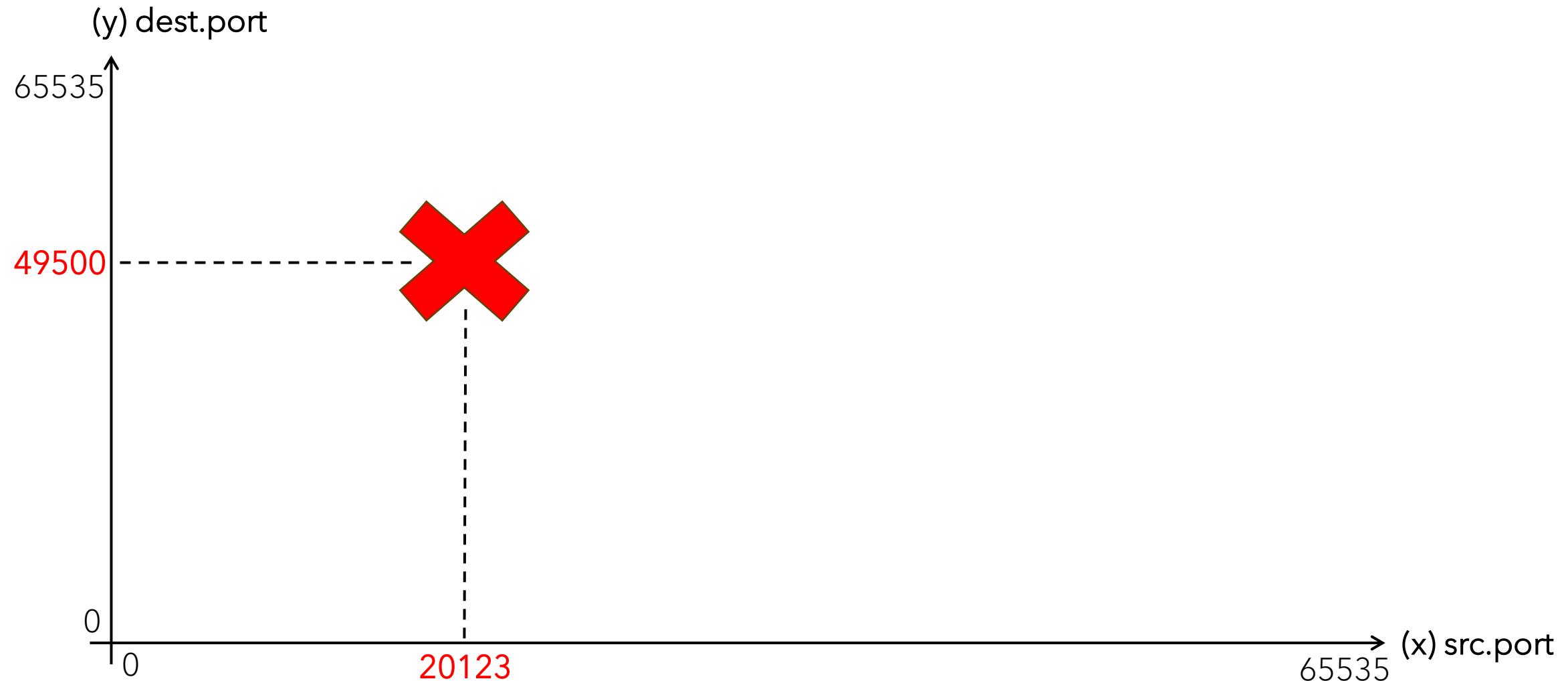
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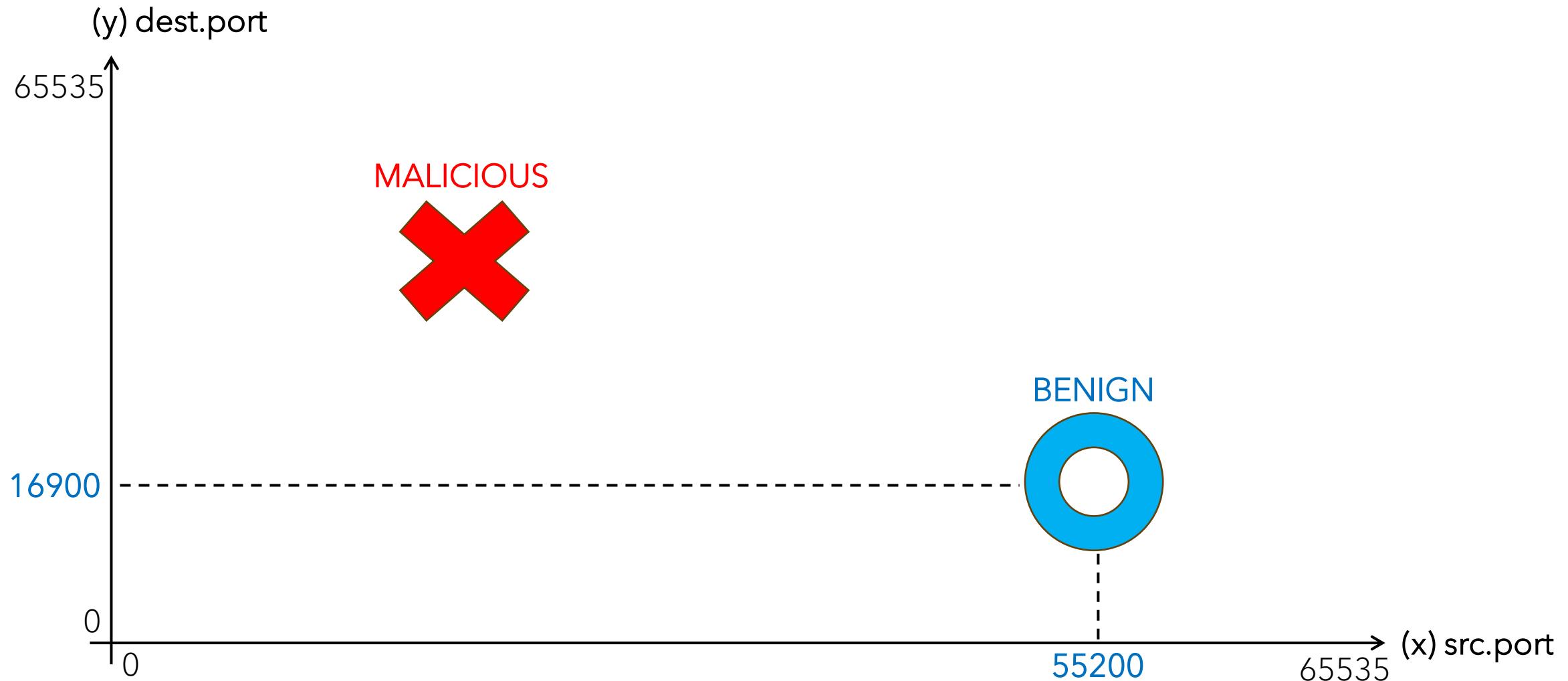
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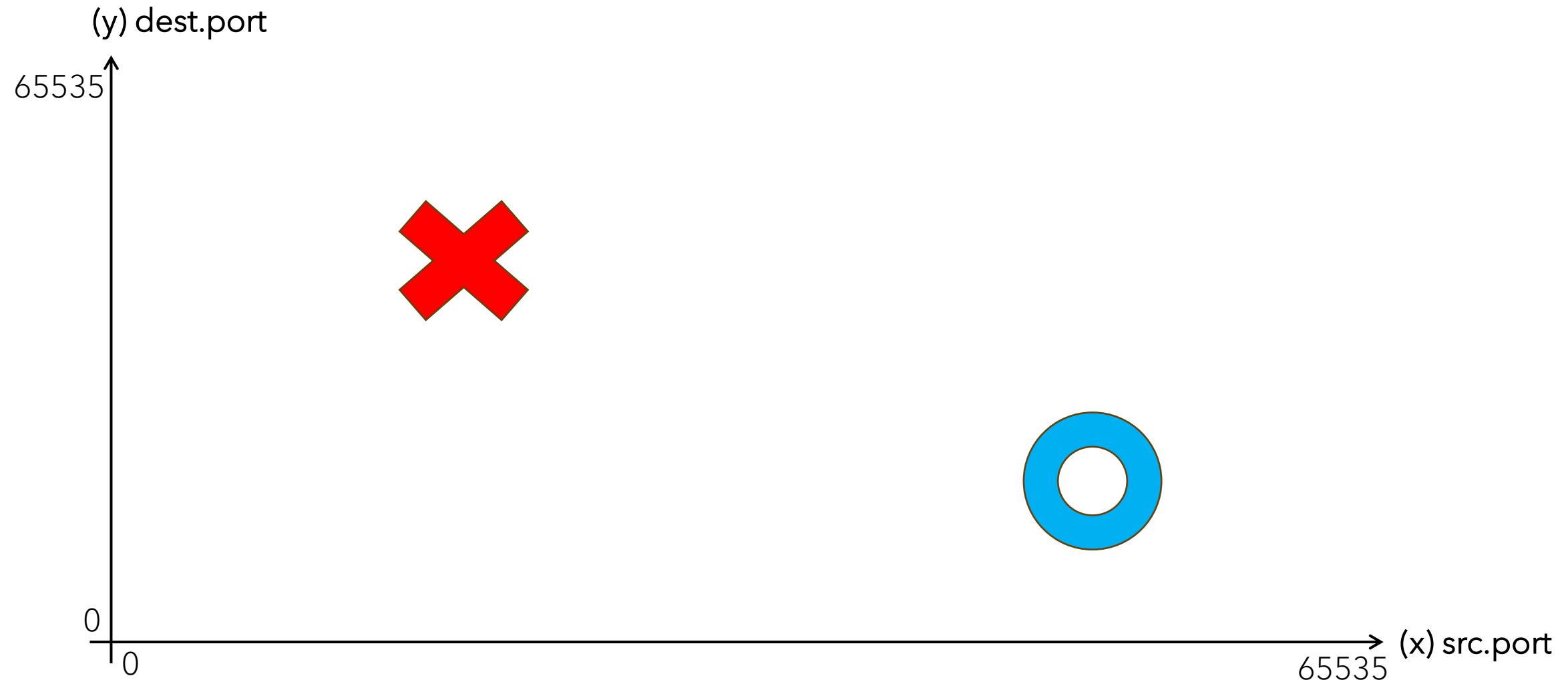
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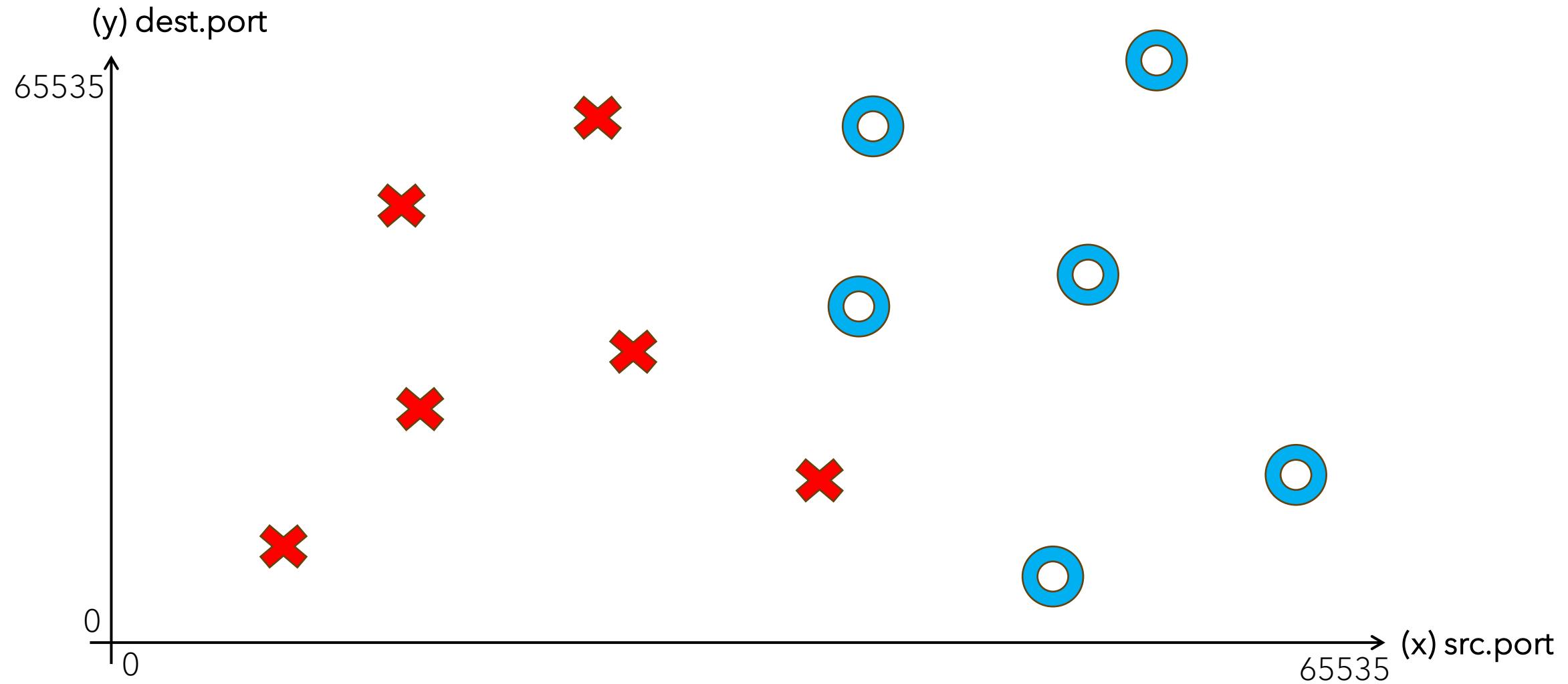
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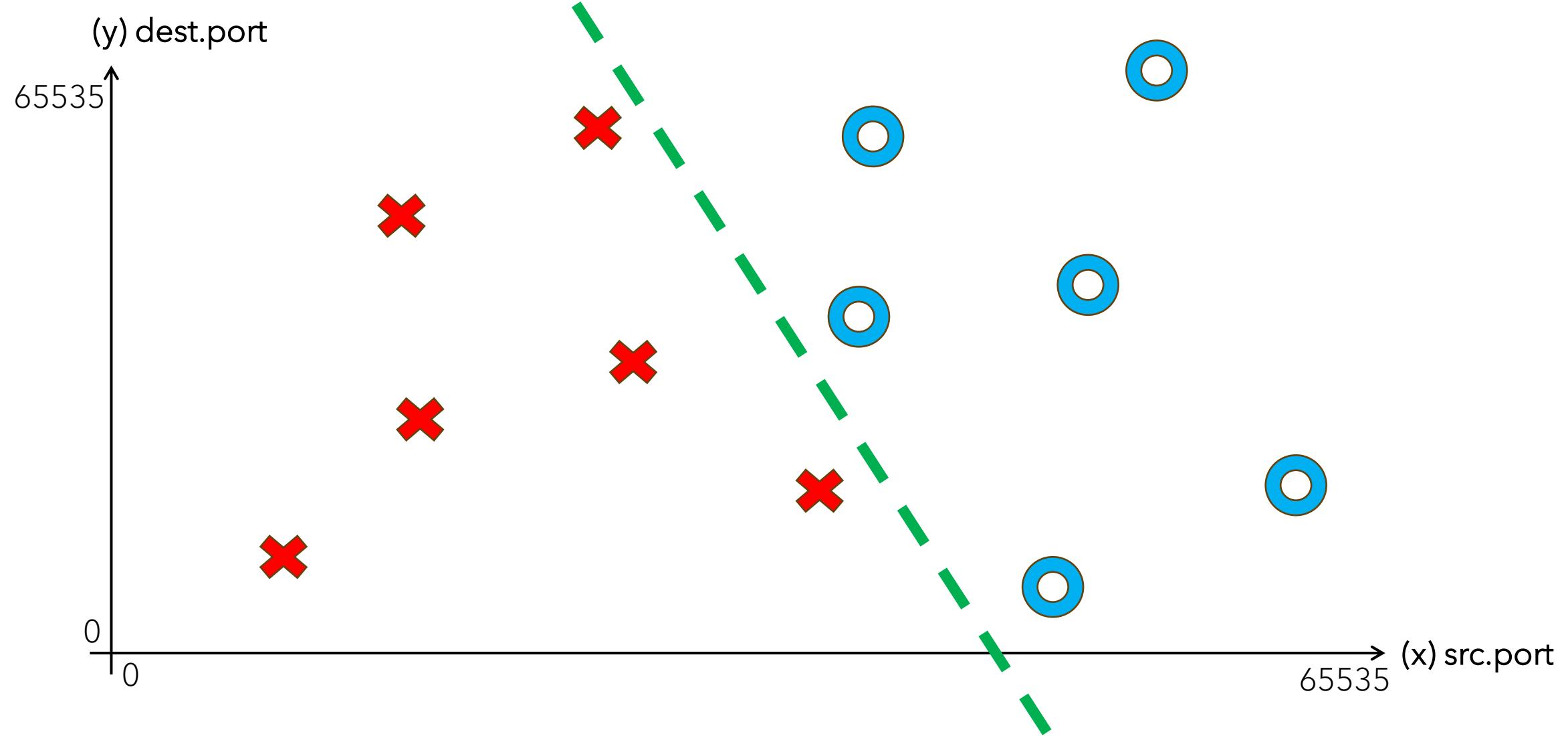
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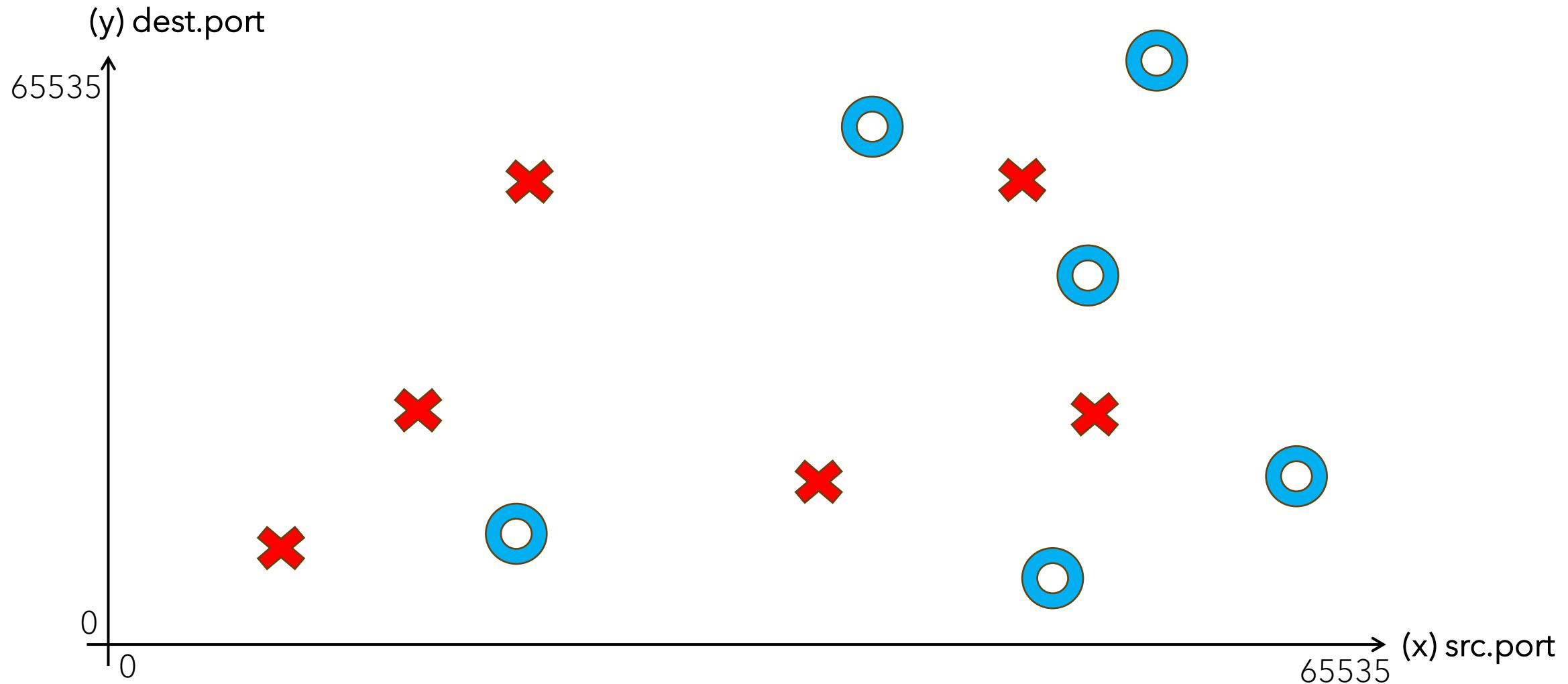
TREINAMENTO - PROBLEMA SIMPLES, SOLUÇÃO LINEARMENTE SEPARÁVEL



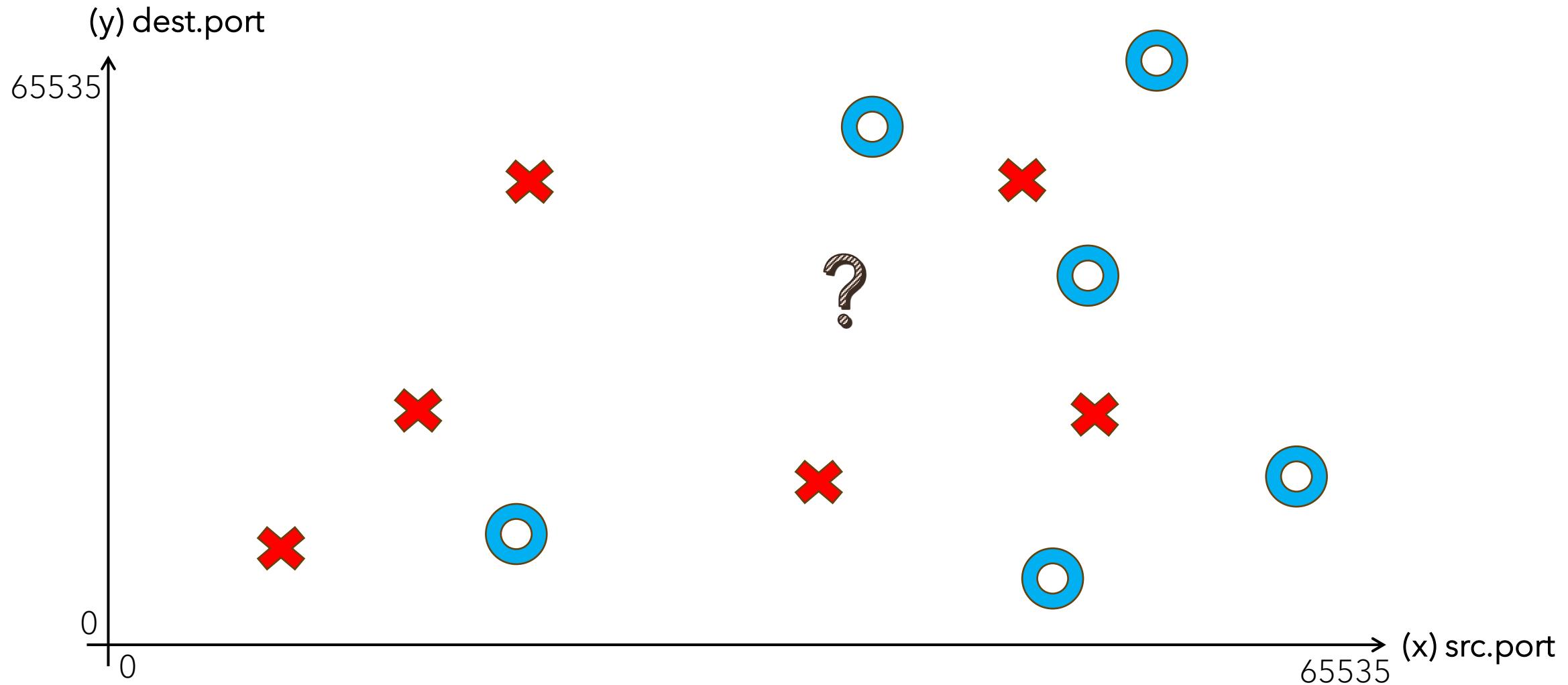
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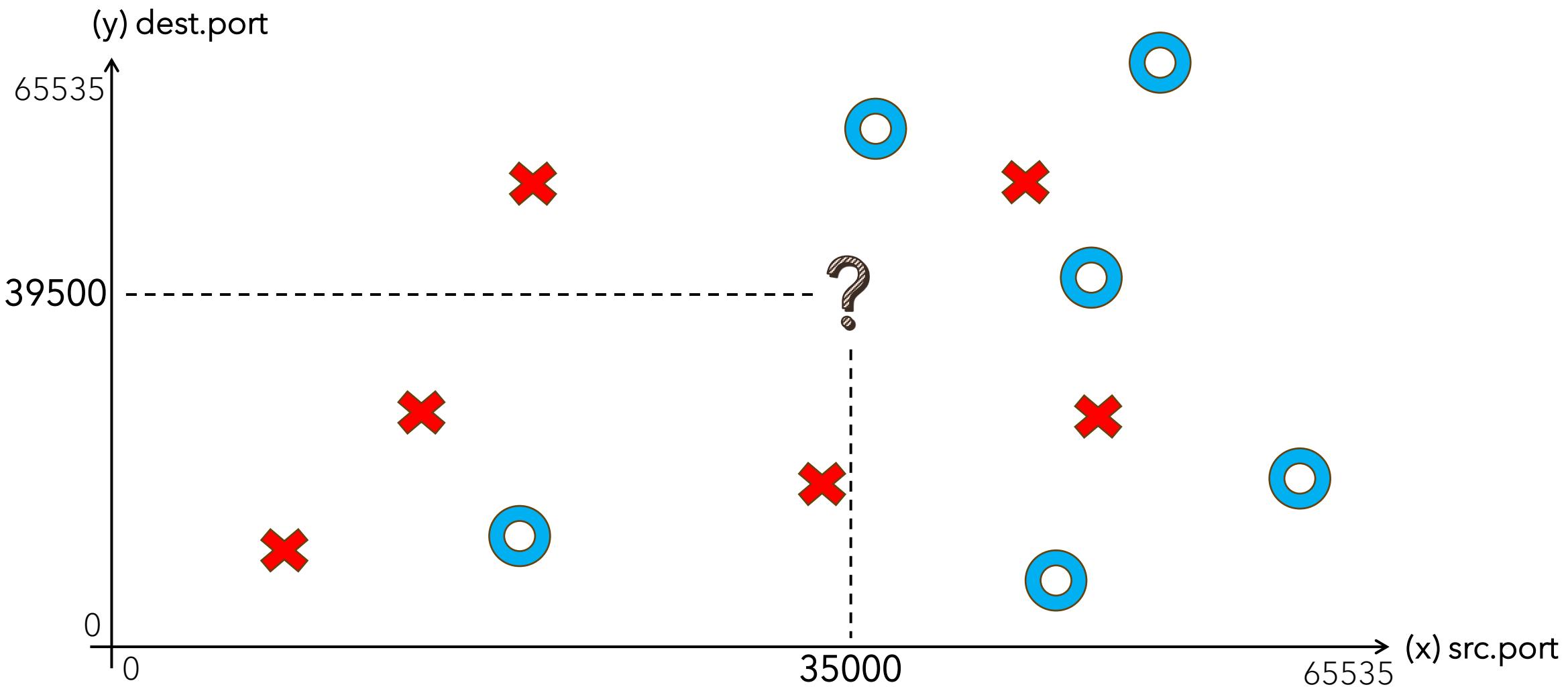
TREINAMENTO - PROBLEMAS COMPLEXOS



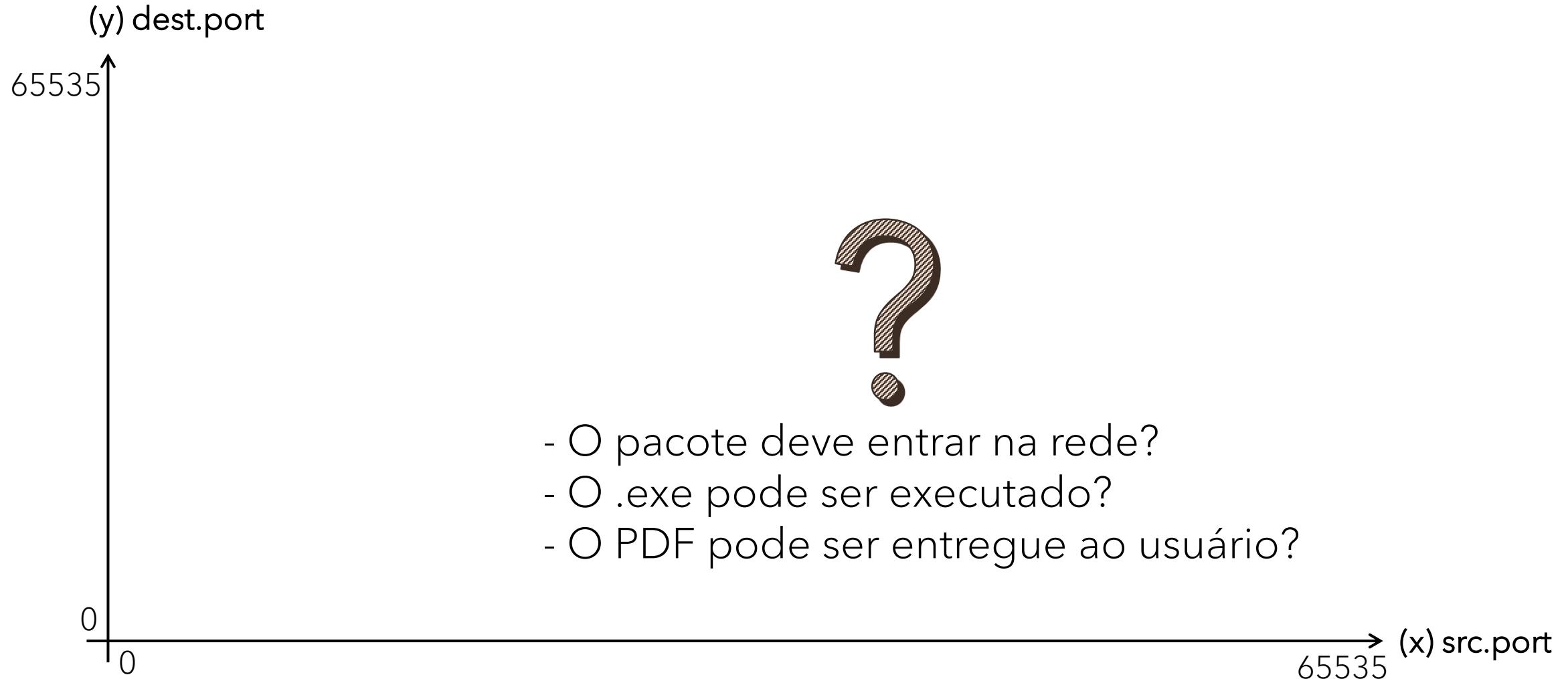
TREINAMENTO - PROBLEMAS COMPLEXOS



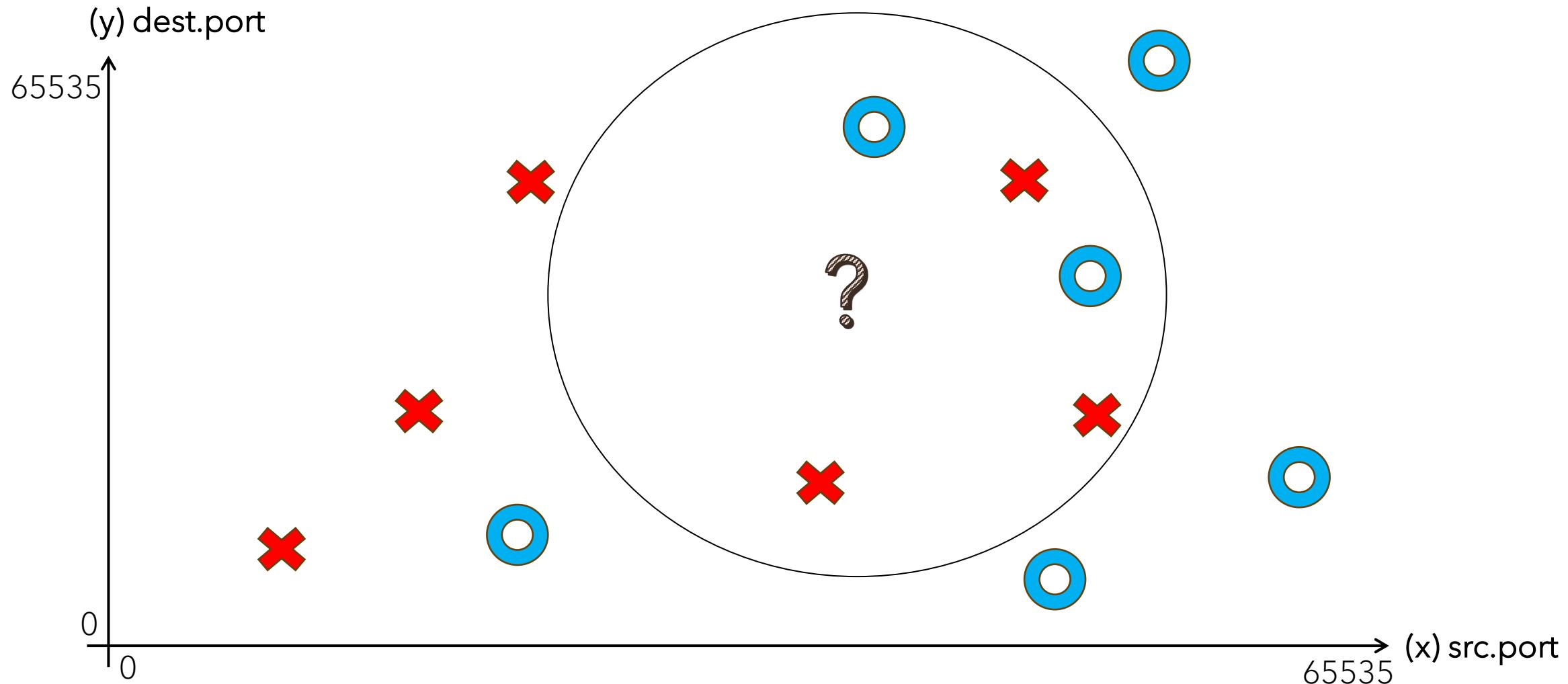
TREINAMENTO - PROBLEMAS COMPLEXOS



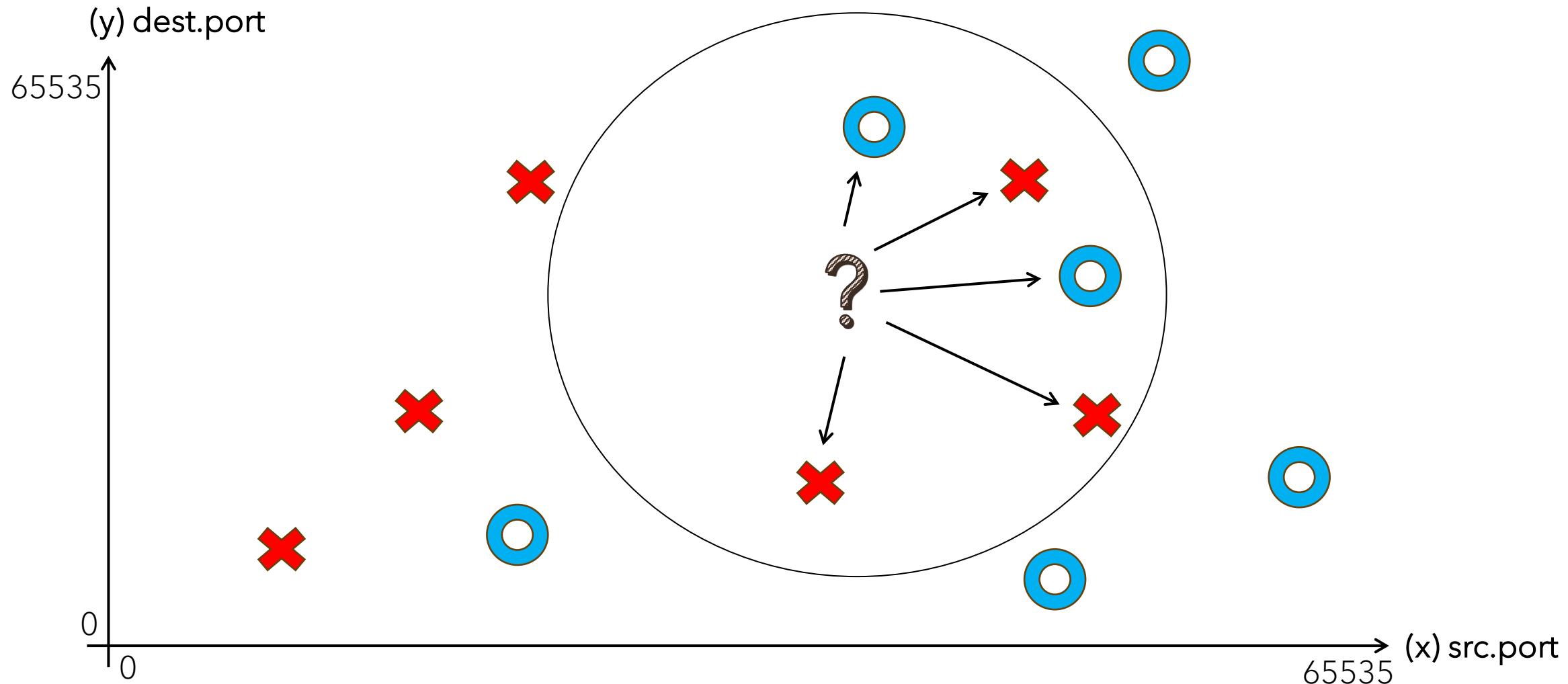
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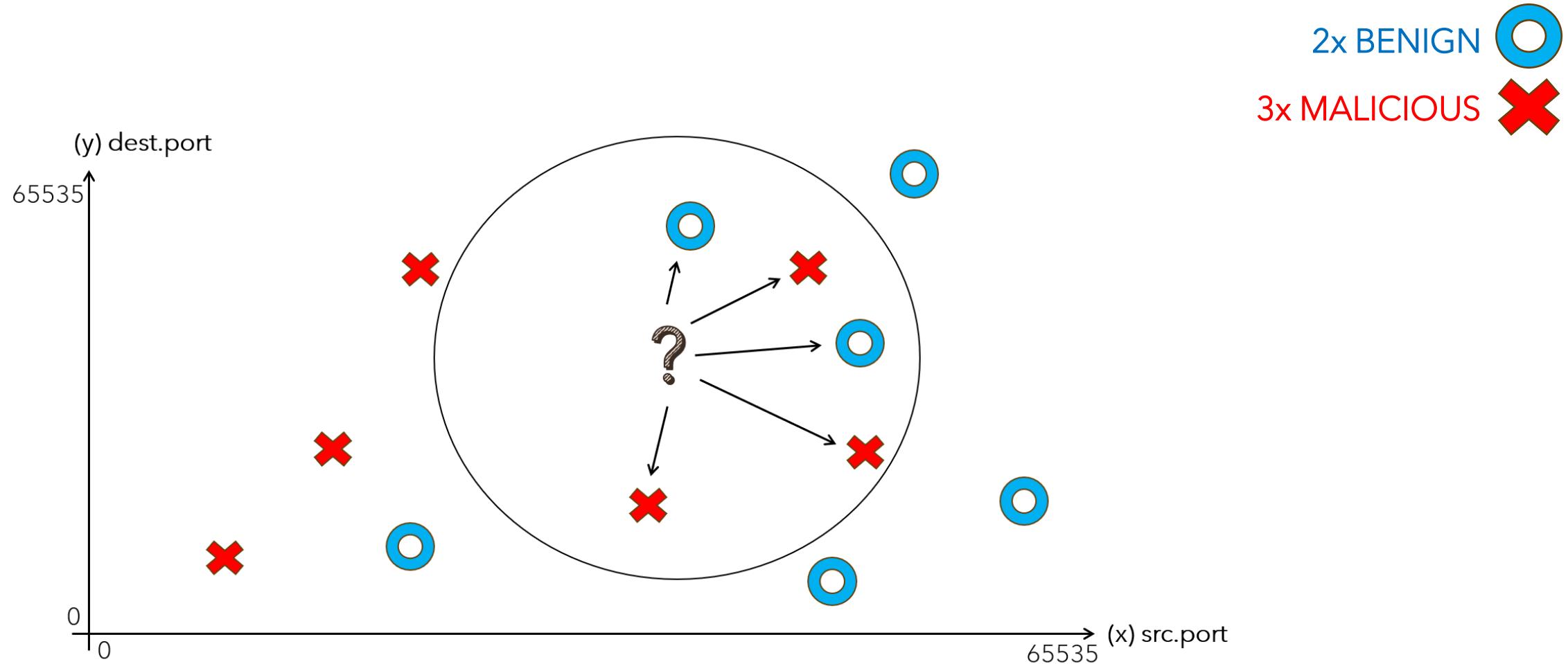
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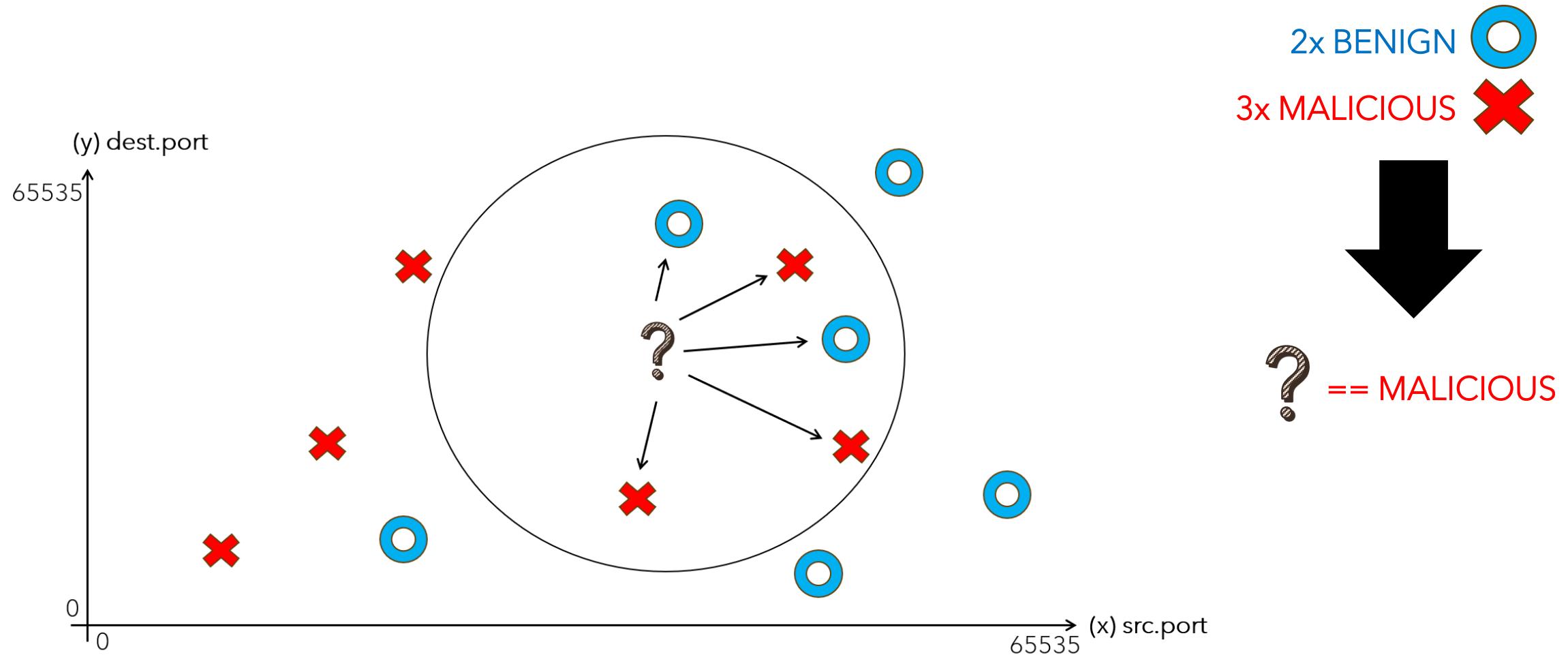
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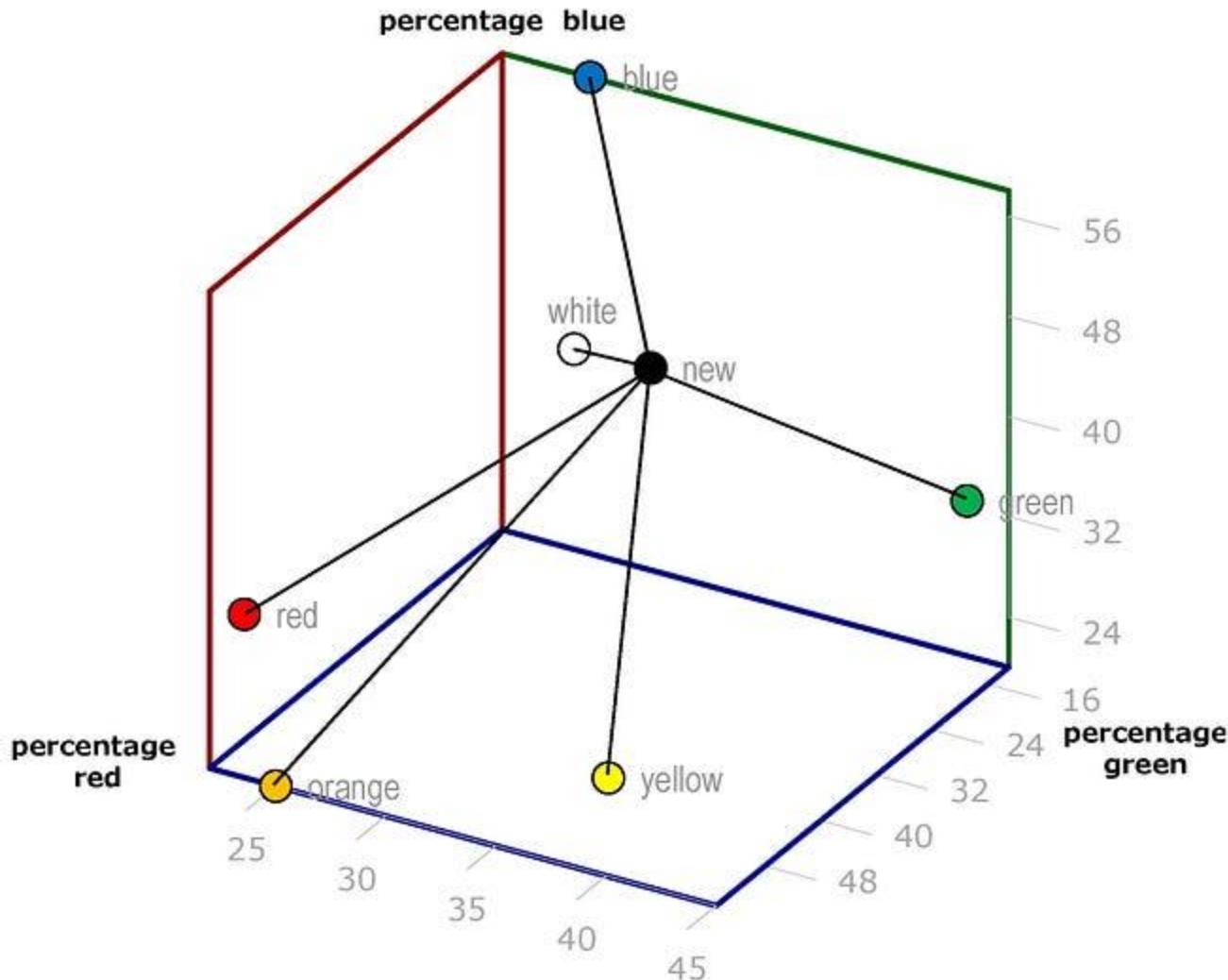
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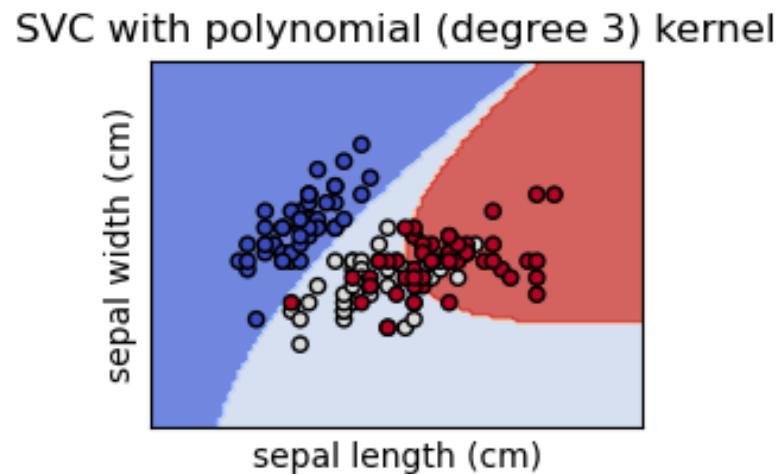
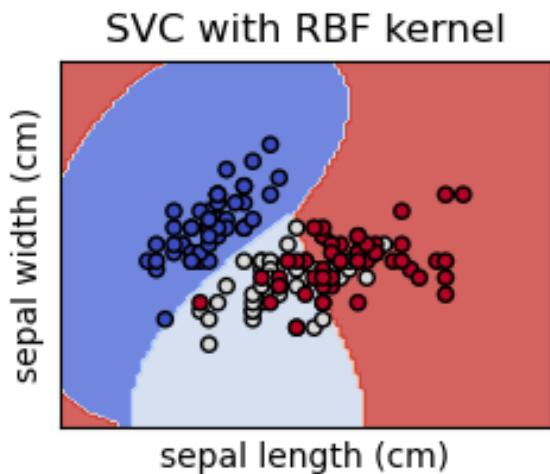
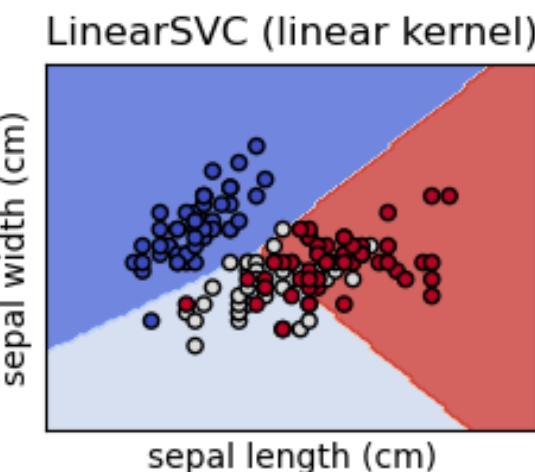
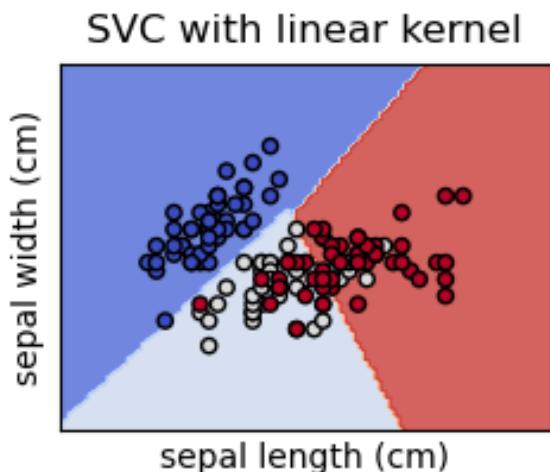
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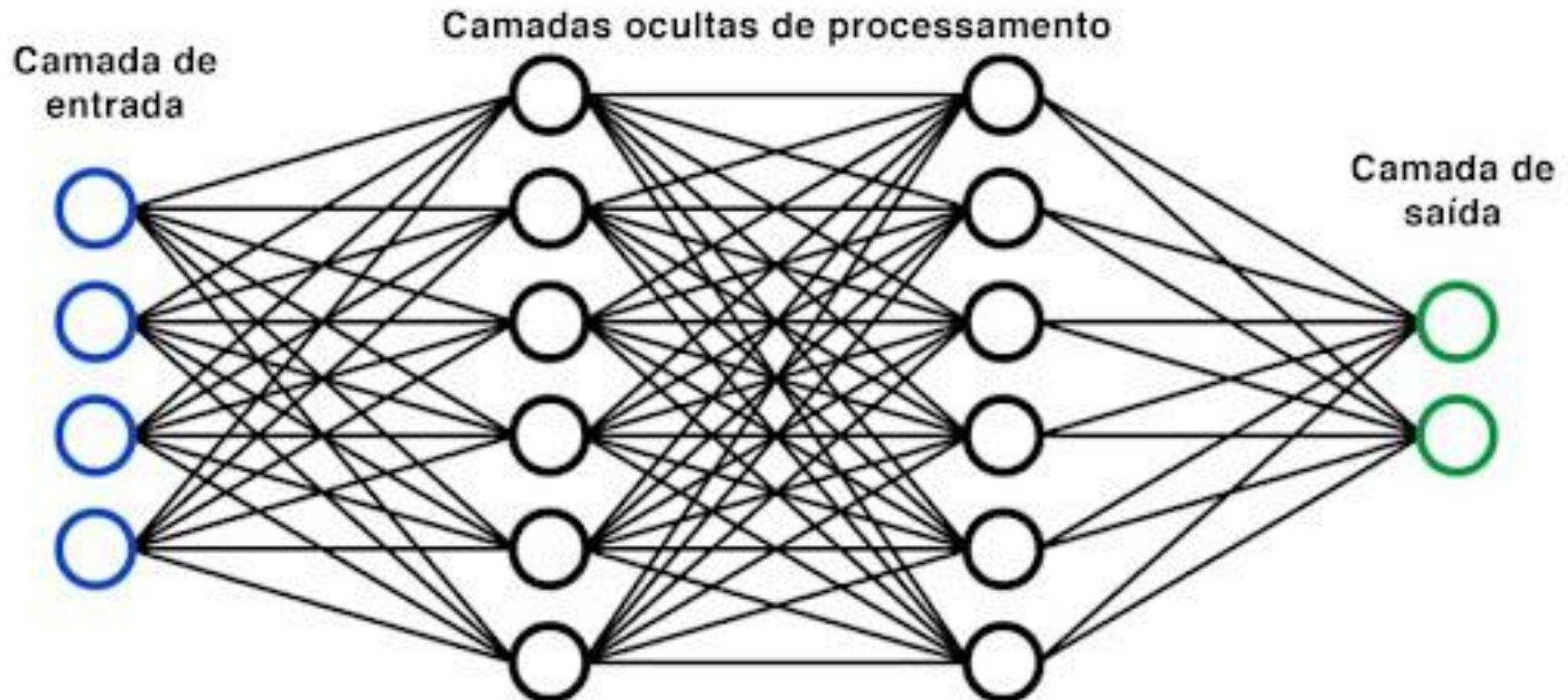
TREINAMENTO - PROBLEMAS COMPLEXOS



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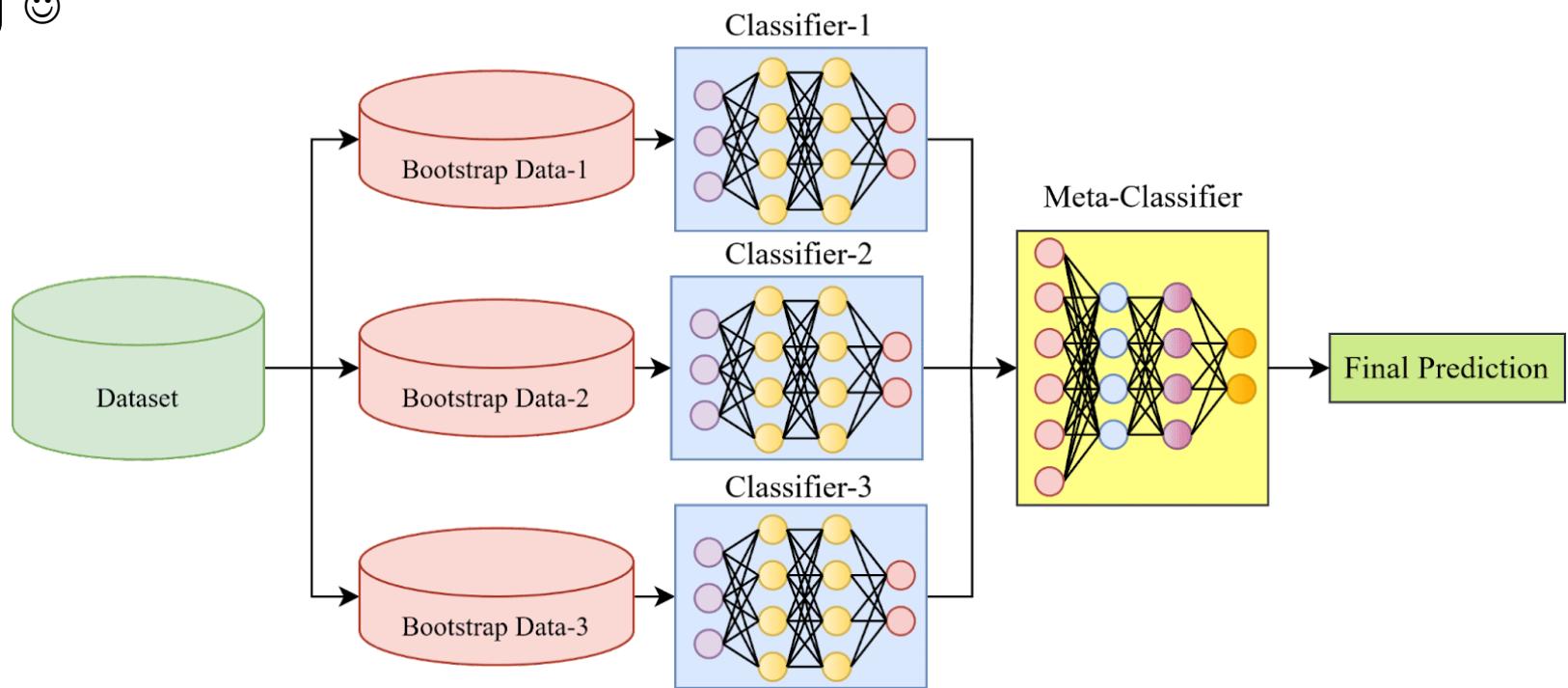


TREINAMENTO - PROBLEMAS COMPLEXOS

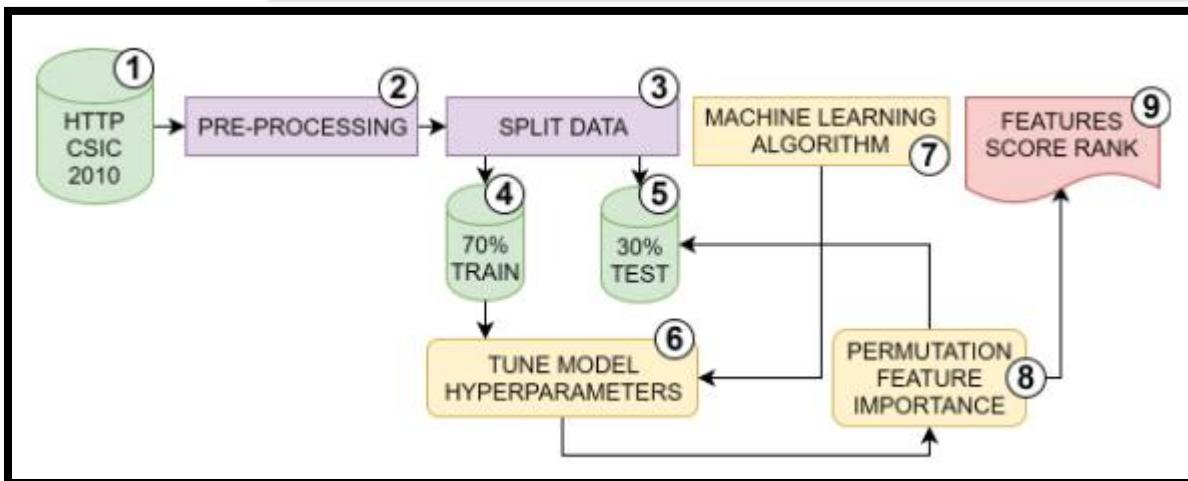


TREINAMENTO - PROBLEMAS + COMPLEXOS AINDA 😊

- Ensemble Learning
- Custo computacional 😞
- Ensemble Pruning 😊



ALGUNS RESULTADOS INTERESSANTES...



Algorithm	Accuracy		Precision		Recall		F1-Score	
SVM	0.95	0.98	0.94	0.97	0.92	0.97	0.93	0.97
BPM	0.90	0.97	0.89	0.98	0.87	0.94	0.88	0.96
AP	0.83	0.96	0.8	0.96	0.79	0.95	0.78	0.95
NN	0.84	0.99	0.83	0.99	0.82	0.98	0.79	0.99
DF	0.66	0.77	0.68	0.90	0.69	0.56	0.64	0.69
DJ	0.62	0.70	0.63	0.88	0.60	0.43	0.62	0.57
BDT	0.64	0.88	0.65	0.94	0.68	0.78	0.65	0.85
LR	0.97	0.97	0.92	0.97	0.95	0.96	0.96	0.97
	mRMR	PFI	mRMR	PFI	mRMR	PFI	mRMR	PFI

ALGUNS RESULTADOS INTERESSANTES...

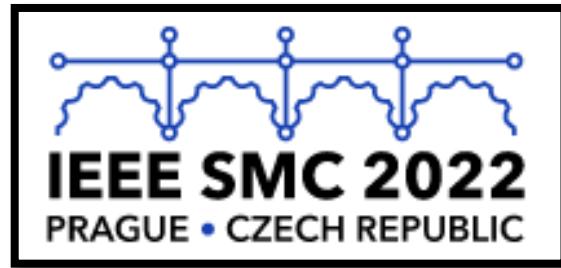


Tabela 4. Compilado com todas as taxas de erro individuais e com o *Stacking* escolhido pela aplicação da combinação proposta pelo autor organizados de acordo com os ataques. Fonte: Elaborado pelo autor.

Classificador	Bruteforce	Infiltration	DDoS	Portscan	Botnet	Web
Stackings	0.017%	0.008%	0.053%	0.026%	0.196%	0.031%
k-NN	0.018%	0.009%	0.085%	0.044%	0.282%	0.032%
DT	0.029%	0.011%	0.053%	0.031%	0.210%	0.049%
SVM	0.528%	0.131%	1.250%	0.464%	0.478%	1.256%
MLP	0.235%	0.131%	0.320%	0.408%	0.448%	0.161%

Attack (dataset)	Exaustion (seconds)	Exaustion (hours)
Brute-force	265145	73.6
Infiltration	62527	17.3
DDoS	361117	100.3
Portscan	415095	115.3
Botnet	67429	18.3
Web	104576	29.04

ALGUNS RESULTADOS INTERESSANTES...



ERROR RATE COMPARISON BETWEEN INDIVIDUAL CLASSIFIERS AND
OUR APPROACH

Approach	Brute-force	Infiltration	DDoS	Portscan	Botnet	Web
Our	0.018%	0.008%	0.629%	0.029%	0.202%	0.032%
k-NN	0.018%	0.009%	0.085%	0.044%	0.282%	0.032%
DT	0.029%	0.011%	0.053%	0.031%	0.210%	0.049%
SVM	0.528%	0.131%	1.250%	0.464%	0.478%	1.256%
MLP	0.235%	0.131%	0.320%	0.408%	0.448%	0.161%

TABLE II
TIME RATIO (COMPUTATIONAL COST IN SECONDS AND HOURS) TO
OBTAIN THE BEST COMMITTEES THROUGH EXHAUSTION, THROUGH
DIVERSITY PRUNING AND THE DIFFERENCE (GAIN) BY OUR APPROACH.

Attack (dataset)	Exaustion (seconds)	Exaustion (hours)	Diversity (seconds)	Diversity (hours)	Difference (hours)
Brute-force	265145	73.6	8889	2.4	-71.18
Infiltration	62527	17.3	291	0.08	-17,28
DDoS	361117	100.3	15761	4.3	-95.93
Portscan	415095	115.3	19912	5.5	-109.77
Botnet	67429	18.3	684	0.19	-18.54
Web	104576	29.04	2272	0.6	-28.41

ALGUNS RESULTADOS INTERESSANTES...



Approach	TN	FP	FN	TP	Sum of errors ↑
KDD-Cup'99					
Diversity	97114	162	1473	395270	1635
KNN	97047	229	1783	394960	2012
DT	96772	504	3032	393711	3536
MLP	96591	685	3800	392943	4485
SVM	96346	930	5222	391521	6152
NSL-KDD					
Diversity	935	61	44	147476	105
DT	910	86	57	147463	143
KNN	806	190	109	147411	299
MLP	759	237	133	147387	370
SVM	258	738	414	147106	1152
UNSW-NB15					
Diversity	63284	29716	4788	159885	34504
k-NN	50089	42911	1853	162820	44764
DT	65134	27866	19723	144950	47589
MLP	54096	38904	9741	154932	48645
SVM	62801	30199	31221	133452	61420
ISCX-IDS-2012					
Diversity Pruning	20585	3550	491	756857	4041
MLP	19008	5127	3351	753997	8478
KNN	20228	3907	11154	746194	15061
SVM	15452	8683	14458	742890	23141
DT	20346	3789	23080	734268	26869

ALGUNS RESULTADOS INTERESSANTES...



Approach	Train time	Test time	Train gain	Test gain
KDD-Cup'99				
Exhaustion	267,435s	3m21s	–	–
Diversity	3,508s	231 ms	–98.69%	–99.89%
NSL-KDD				
Exhaustion	245,908s	2m33s	–	–
Diversity	2,542s	157 ms	–98.97%	–99.91%
UNSW-NB15				
Exhaustion	377,119s	6m07s	–	–
Diversity	6,004s	499 ms	–98.41%	–99.87%
ISCX-IDS-2012				
Exhaustion	658,546s	7m36s	–	–
Diversity	9,774s	576 ms	–98.41%	–99.86%

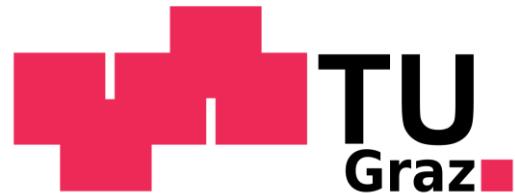
ALGUNS RESULTADOS INTERESSANTES...

31st IWSSIP – International Conference on Systems, Signals and Image Processing 2024

9th – 11th of JULY, 2024, IEEE Technical Co-Sponsored Conference

Graz University of Technology, Inffeldgasse 12, A-8010 Graz, AUSTRIA,

Approach	Accuracy ↓	AUC	Precision	Recall	F1-Score
KDD-Cup'99					
Diversity	99.669%	99.731%	99.959%	99.629%	99.794%
<i>k</i> -NN	99.593%	99.658%	99.942%	99.551%	99.746%
DT	99.284%	99.359%	99.872%	99.236%	99.553%
MLP	99.092%	99.169%	99.826%	99.042%	99.433%
SVM	98.755%	98.864%	99.763%	98.684%	99.220%
NSL-KDD					
Diversity	99.929%	96.923%	99.959%	99.970%	99.964%
DT	99.904%	95.663%	99.942%	99.961%	99.952%
<i>k</i> -NN	99.799%	90.425%	99.871%	99.926%	99.899%
MLP	99.751%	88.057%	99.839%	99.910%	99.875%
SVM	99.224%	62.811%	99.501%	99.719%	99.610%
UNSW-NB15					
Diversity	86.609%	82.570%	84.327%	97.092%	90.261%
<i>k</i> -NN	82.628%	76.367%	79.142%	98.875%	87.915%
DT	81.531%	79.030%	83.875%	88.023%	85.899%
MLP	81.121%	76.126%	79.929%	94.085%	86.431%
SVM	76.164%	74.284%	81.547%	81.041%	81.293%
ISCX-IDS 2012					
Diversity	99.483%	92.613%	99.533%	99.935%	99.734%
MLP	98.915%	89.157%	99.325%	99.558%	99.441%
<i>k</i> -NN	98.073%	91.170%	99.479%	98.527%	99.001%
SVM	97.039%	81.057%	98.845%	98.091%	98.466%
DT	96.562%	90.627%	99.487%	96.953%	98.203%



ALGUNS RESULTADOS INTERESSANTES...



22º Congresso Latino-americano de
Software Livre e Tecnologias Abertas



Machine Learning-based Spyware Detection
Systems: An Undersampling Performance Analysis

Large Language Models for Intrusion Detection:
Tokenization Impacts on DDoS Flows

Interpretability of Intrusion Detection Models:
An Information Visualization Approach

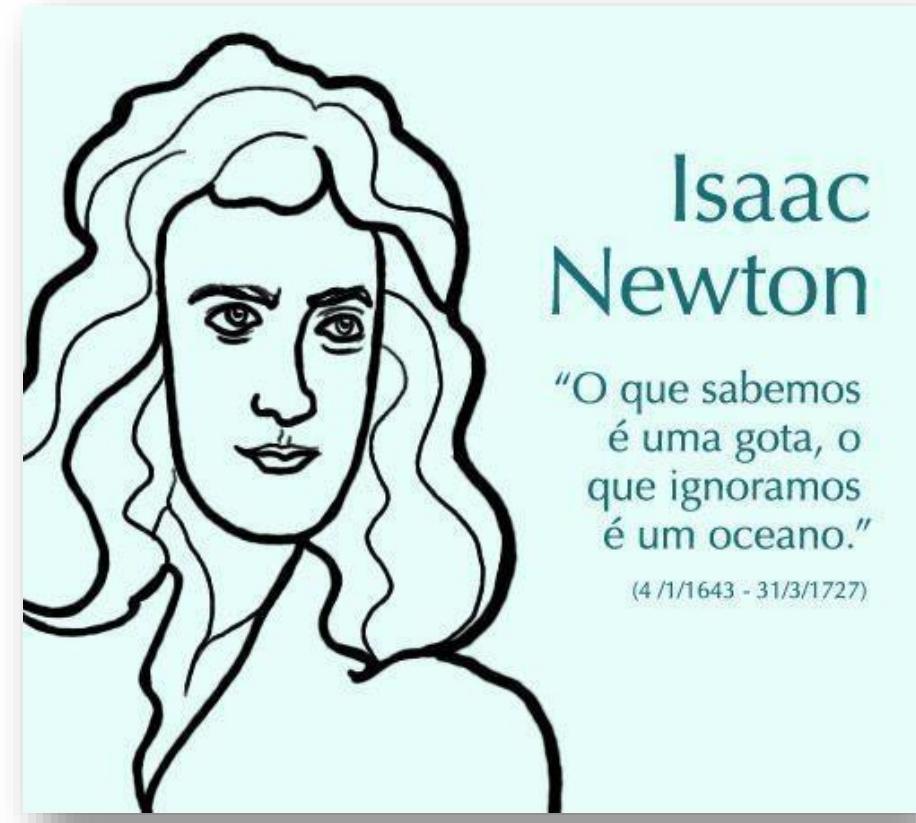
Evaluation of Machine Learning Algorithms for
Intrusion Detection in SCADA Systems

Detection of SQL Injection: A Comparative Analysis
of Machine Learning and Deep Learning Algorithms

Comparative Evaluation of Supervised Machine
Learning Algorithms for Intrusion Detection in
Electric Vehicle Systems

QUAIS AS CONCLUSÕES?

- Os ataques evoluíram muito
 - Pentest é muuuuito mais atrativo
- Blue Team precisa evoluir
 - I.A. aplicada a segurança defensiva é realidade!
- Red Team pode pensar nas IAs generativas 😊



OBRIGADO!



A circular profile picture of a man with a beard and short dark hair, wearing a black t-shirt. He is gesturing with his hands while speaking. To his right is a composite image featuring a white silhouette of a person's head and shoulders, a blue background with abstract digital patterns like circuit boards and network nodes, and several smartphone icons.

Thiago José Lucas 

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