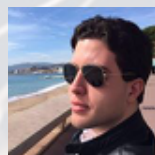
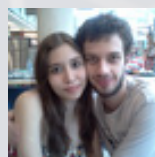


## Regressor de Qualidade das Vias

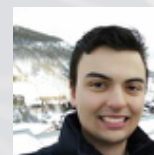


Carlos Grivol

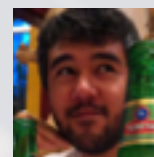


Carlos Prete

## Reconhecedor de Moedas



Gabriel Crabbé



Tiago Amano

# Regressor: Motivação

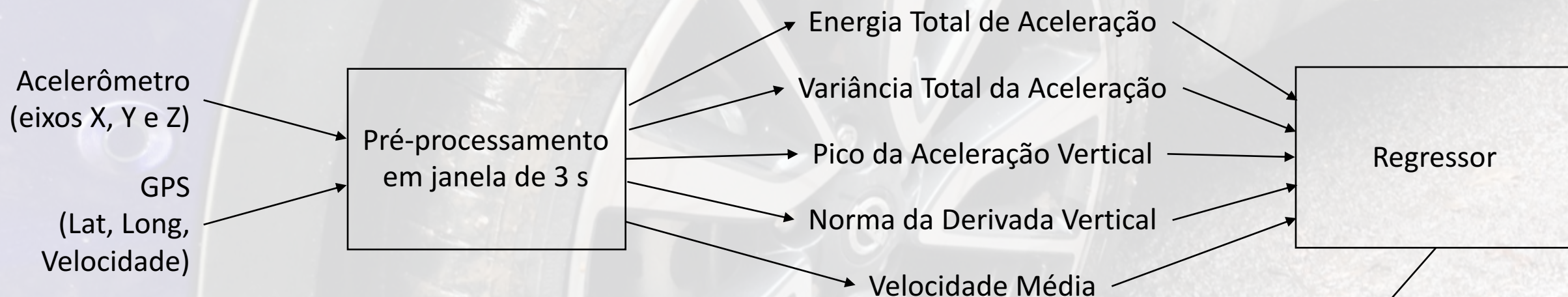
De acordo com a Prefeitura de São Paulo, em 2015 foram utilizados **R\$ 110 milhões** para recapear **135,5 km** de vias e tapar **294.419 buracos** na cidade, que apresenta uma malha viária de mais de **17 mil km** de vias pavimentadas.



Simultaneamente, o número de solicitações de **reparos cresceu 21%** (de 54.074 para 65.459 solicitações).



# Regressor: Regressor de Qualidade das Vias



Escala PASER  
da Universidade de  
Wisconsin—Madison

Índice de  
Qualidade do  
Pavimento  
(1 a 10)

# Regressor: Escala PASER



## RATINGS ARE RELATED TO NEEDED MAINTENANCE OR REPAIR

Rating 9 & 10	No maintenance required
Rating 8	Little or no maintenance
Rating 7	Routine maintenance, cracksealing and minor patching
Rating 5 & 6	Preservative treatments (sealcoating)
Rating 3 & 4	Structural improvement and leveling (overlay or recycling)
Rating 1 & 2	Reconstruction

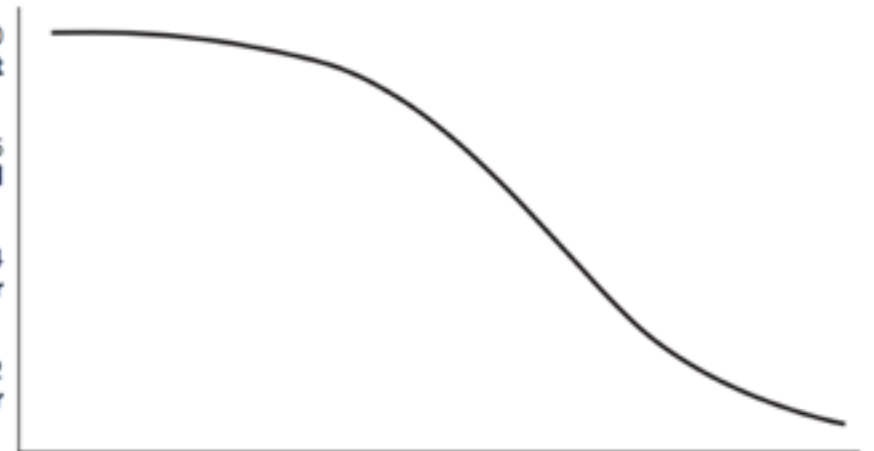
PAVEMENT CONDITION

RATING 10  
**Excellent**

RATING 6  
**Good**

RATING 4  
**Fair**

RATING 2  
**Poor**

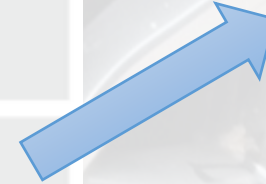


PAVEMENT AGE →



# Regressor: Escala PASER

Surface rating	Visible distress*	General condition/ treatment measures
<b>10</b> Excellent	None.	New construction.
<b>9</b> Excellent	None.	Recent overlay. Like new.
<b>8</b> Very Good	No longitudinal cracks except reflection of paving joints. Occasional transverse cracks, widely spaced (40' or greater). All cracks sealed or tight (open less than 1/4").	Recent sealcoat or new cold mix. Little or no maintenance required.
<b>7</b> Good	Very slight or no raveling, surface shows some traffic wear. Longitudinal cracks (open 1/4") due to reflection or paving joints. Transverse cracks (open 1/4") spaced 10' or more apart, little or slight crack raveling. No patching or very few patches in excellent condition.	First signs of aging. Maintain with routine crack filling.
<b>6</b> Good	Slight raveling (loss of fines) and traffic wear. Longitudinal cracks (open 1/4"–1/2"), some spaced less than 10'. First sign of block cracking. Slight to moderate flushing or polishing. Occasional patching in good condition.	Shows signs of aging. Sound structural condition. Could extend life with sealcoat.



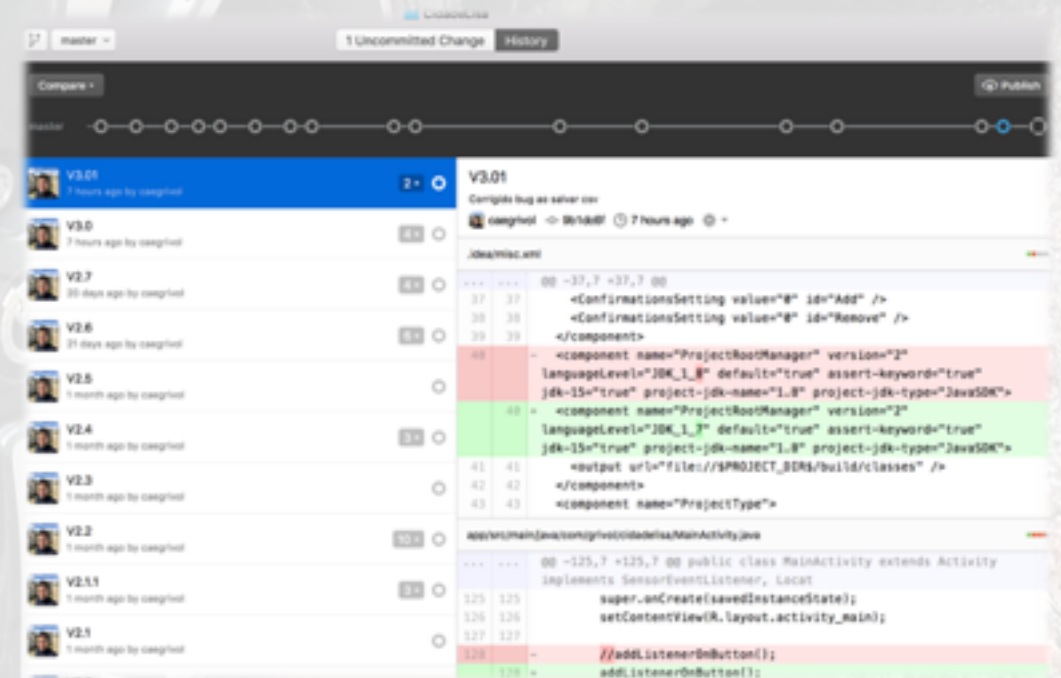
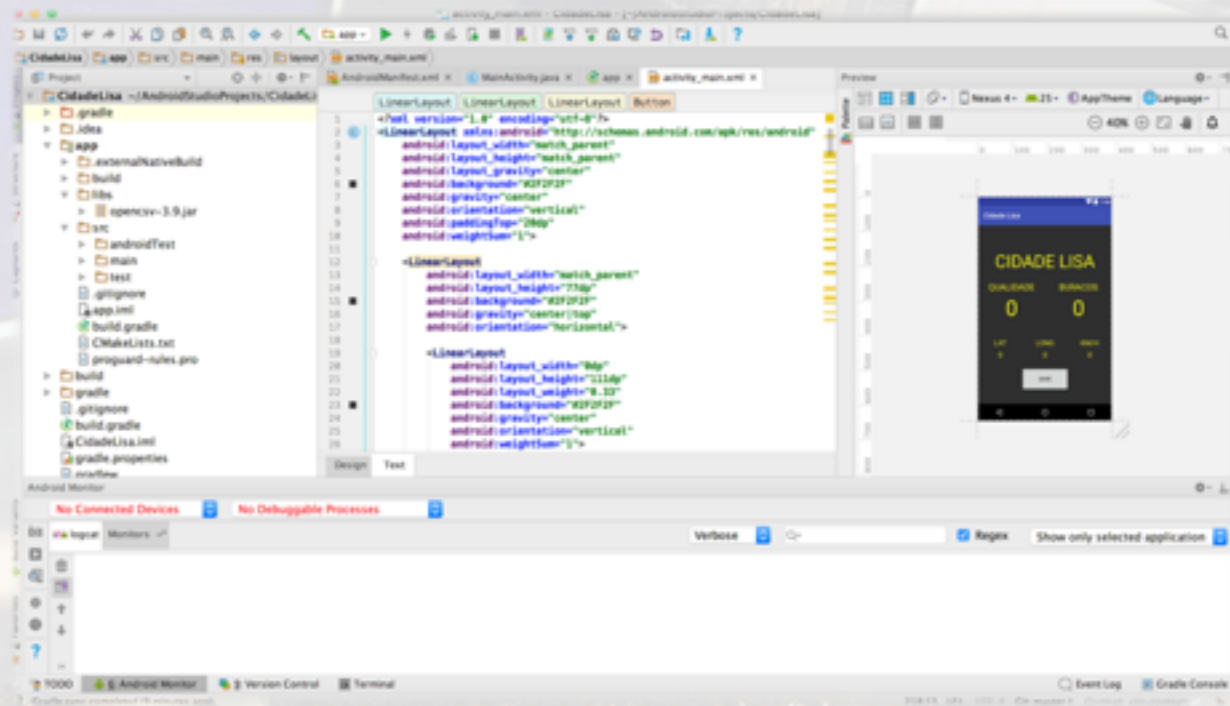
# Regressor: Escala PASER

Surface rating	Visible distress*	General condition/ treatment measures
<b>5</b> Fair	Moderate to severe raveling (loss of fine and coarse aggregate). Longitudinal and transverse cracks (open 1/2") show first signs of slight raveling and secondary cracks. First signs of longitudinal cracks near pavement edge. Block cracking up to 50% of surface. Extensive to severe flushing or polishing. Some patching or edge wedging in good condition.	Surface aging. Sound structural condition. Needs sealcoat or thin non-structural overlay (less than 2")
<b>4</b> Fair	Severe surface raveling. Multiple longitudinal and transverse cracking with slight raveling. Longitudinal cracking in wheel path. Block cracking (over 50% of surface). Patching in fair condition. Slight rutting or distortions (1/2" deep or less).	Significant aging and first signs of need for strengthening. Would benefit from a structural overlay (2" or more).
<b>3</b> Poor	Closely spaced longitudinal and transverse cracks often showing raveling and crack erosion. Severe block cracking. Some alligator cracking (less than 25% of surface). Patches in fair to poor condition. Moderate rutting or distortion (1" or 2" deep). Occasional potholes.	Needs patching and repair prior to major overlay. Milling and removal of deterioration extends the life of overlay.
<b>2</b> Very Poor	Alligator cracking (over 25% of surface). Severe distortions (over 2" deep). Extensive patching in poor condition. Potholes.	Severe deterioration. Needs reconstruction with extensive base repair. Pulverization of old pavement is effective.
<b>1</b> Failed	Severe distress with extensive loss of surface integrity.	Failed. Needs total reconstruction.





# Regressor: Desenvolvimento do App





# Regressor: Coleta de dados





# Regressor: Tratamento de Dados

Exemplo de log

The image shows a file explorer window on the left with a list of CSV files. The files are organized into folders: CLASSE1, CLASSE2, and CLASSE3. Each file has a date and time stamp. Two blue arrows point from the CSV files to a Java code snippet on the right. The code snippet is a Java class named TrainDataParser, which is used to parse CSV files and write the data to a text file. The code includes imports for java.io.File, java.io.FileNotFoundException, java.io.PrintWriter, and java.util.Scanner. It also includes a main method that takes command line arguments and throws a FileNotFoundException.

	A	B	C	D	E	F	G	H	I	J
1	AccelerationX	-0.307	1.301	-0.077	0.267	-1.3030001	-0.345	-1.3410001	0.267	0.038000003
2	AccelerationY	-0.9189997	-1.1869993	-0.4979992	0.03900051	-0.88099957	-1.7229996	-0.9569998	-0.037999153	-0.22899914
3	AccelerationZ	1.8009999	1.4559999	-0.153	-0.574	-0.99600005	0.4979999	-0.037999988	1.4559999	0.19199991
4	Speed	29.647999	29.647999	30.315079	30.315079	30.315079	30.315079	30.315079	30.315079	30.315079
5	AverageSpeed	30.567627	EventOrder	0	Latitude	-23.619678333333333	Longitude	-46.69822666666667		
6	AverageX	-0.20152001	AverageY	-0.6439195	AverageZ	0.40875998				
7	MinX	-1.763	MinY	-2.0299997	MinZ	-1.149				
8	MaxX	1.301	MaxY	1.1500006	MaxZ	2.299				
9	StdX	0.70752364	StdY	0.81862694	StdZ	0.83702767				
10	GravityX	-0.114	GravityY	9.921	GravityZ	1.608				

```
package traindataparser;

import java.io.File;
import java.io.FileNotFoundException;
import java.io.PrintWriter;
import java.util.Scanner;

/**
 *
 * @author Carlos Eduardo Grivol Júnior
 */
public class TrainDataParser {

    /**
     * @param args the command line arguments
     * @throws java.io.FileNotFoundException
     */
    public static void main(String[] args) throws FileNotFoundException {

        PrintWriter pwr = new PrintWriter(new File("/Users/grivol/Desktop/data.txt"));
        StringBuilder sbr = new StringBuilder();

        File dir = new File("/Users/grivol/Desktop/logs");
        File[] directoryListing = dir.listFiles();

        String[] strArray;

        File tmpFile = directoryListing[0];
        Scanner in = new Scanner(tmpFile);
        StringBuilder sb = new StringBuilder();
```

Pasta com logs coletados

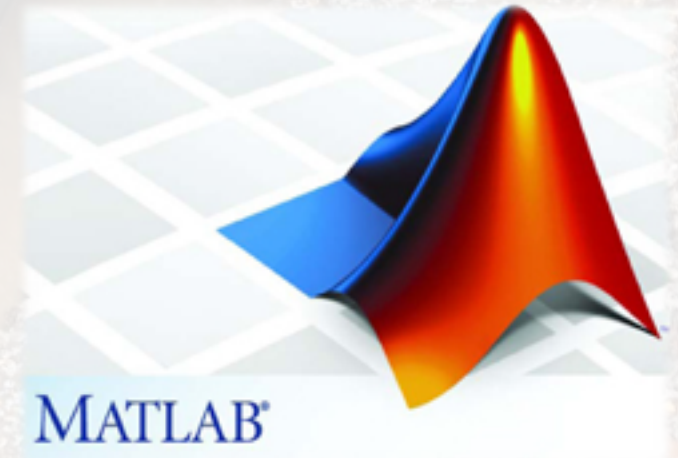
Parser desenvolvido em Java



# Regressor: Tratamento de Dados

I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
MinY	MinZ	MaxX	MaxY	MaxZ	StdX	StdY	StdZ	GravityX	GravityY	GravityZ	AmplX	AmplMaxY	AmplMinY	AmplY	N / Speed	N/K	Class
-0.46	-0.958	0.652	0.7659998	1.079	0.2897824	0.3179609	0.5006886	-0.421	0.442	1.072	1.186	0.67657965	-0.14942019	1.2259998	0.342438838	1.03372668	5
-0.451	0.0769999	0.689	0.6520004	2.49	0.2139784	0.3052168	0.454409	-0.268	0.04	1.302	1.149	0.769960376	-0.539340024	1.3030004	0.348377966	1.134029964	5
-1.4549999	-0.421	0.46	0.3450003	1.1750001	0.3536821	0.412441	0.4893008	-0.574	0.653	1.915	1.878	0.7391201	-1.06068007	1.8000002	0.083715944	0.95844454	5
-1.302	-1.647	1.608	0.5749998	0.766	0.3891636	0.4347067	0.5327241	-1.225	0.880	1.915	1.53200003	0.79400018	-1.08299962	1.8769998	0.056034893	1.22519567	5
-1.302	-3.907	1.178	0.8049994	0.520	0.4424614	0.4254096	0.9953767	-1.225	0.880	1.915	2.22100005	1.05305064	-1.05303971	2.3269994	0.202764797	0.94867146	5
-1.2639999	-3.638	1.8759999	1.3030005	-0.1149999	0.6804523	0.6026958	0.8203865	-0.134	0.610	1.512	3.026	1.211520418	-1.395479984	2.5670004	0.083176129	0.84831478	5
-1.302	-3.6	1.761	1.4560003	1.6470003	0.6611292	0.6179809	0.9905286	-0.421	0.002	2.758	3.34	1.27520005	-1.53880025	2.7580003	0.123363601	0.87834404	5
-1.3789997	-1.494	1.179	1.533	1.264	0.3728875	0.7707375	0.6048797	-0.183	0.610	1.512	1.762	1.506409858	-1.805119842	2.9159997	0.089983487	1.65294725	5
-2.413	0.11500001	1.3399999	0.6520004	3.064	0.3531518	0.7019641	0.6728314	-0.574	0.610	1.519	1.65499991	1.01406035	-1.05094005	3.0650004	0.126839379	2.50652961	5
-1.9160004	-1.799	1.6850002	1.1870003	2.605	0.5002702	0.7083373	0.8907268	-0.268	0.807	0.192	2.7570002	1.31374017	-1.74926033	3.3200007	0.124472729	1.12549894	5
-1.8390002	-1.801	1.034	1.3029995	2.336	0.6091399	0.7918111	0.8371418	-0.076	0.385	1.877	2.6419999	1.51111873	-1.50087987	3.3419997	0.084134506	1.3892305	5
-1.3410006	-2.029	2.451	1.9539995	1.226	0.7290879	0.7623225	0.6674354	-0.574	0.347	0.804	3.14100006	1.51275956	-1.76224054	3.2950001	0.136332255	1.04902898	5
-1.533	-1.37	1.608	2.306	1.1780001	0.723700	0.8106021	1.0532343	-0.268	0.807	0.192	2.757	2.16476009	-1.67423981	3.689	0.104136331	1.33991295	5
-2.0300002	-2.136	2.221	1.8769999	1.609	1.0831652	0.7949805	0.8707642	-0.191	0.385	1.417	4.405	1.72832009	-2.17868001	3.9070001	0.202101739	0.88694467	5
-1.7620001	-1.455	3.467	2.588	2.222	0.9844022	1.0272385	0.9879615	-0.191	0.385	1.417	4.022	1.96782034	-1.97857986	3.5460002	0.0899425	0.98150995	5
-1.8389997	-2.6899998	2.144	2.9130003	2.1220001	0.66477	1.113435	1.2392241	-0.421	0.002	2.758	3.10199994	2.62902014	-2.12007984	4.75	0.175160408	1.53127038	5
-1.9130004	-1.3030001	4.175	3.7539997	3.2159998	0.8652809	1.0693923	1.0835717	-0.191	0.385	1.417	4.098	3.697999866	-1.971900234	5.6690001	0.195680453	1.58331796	5
-2.2719996	-1.447	1.8	3.946	1.532	0.47003	1.5767781	1.041654	-0.306	0.610	1.512	3.375	3.75037988	-2.41763972	6.3679996	0.194401134	2.18702446	5
-0.6899996	-1.484	0.306	0.8039999	0.7280002	0.2158909	0.2688409	0.5754447	-0.344	0.615	2.306	0.97000006	0.90517969	-0.58881981	1.4939995	0.040608941	1.62567944	4
-1.1879997	-1.3019999	0.574	1.1880007	0.6900001	0.5898938	0.5123634	0.4337445	-0.038	0.615	1.8	3.335	1.311300396	-1.064700004	2.3760004	0.076277938	1.01751806	4
-0.6899996	-1.483	1.646	1.724	2.060	0.4130524	0.6805179	0.7869961	-0.804	0.442	0.129	2.45	1.313579376	-1.10041984	2.4139996	0.175272846	0.98530596	4
-1.6089997	-0.9919999	1.646	1.3403006	2.9130003	0.6127503	0.6784363	0.9442563	-0.344	0.442	1.494	2.7570001	1.41558052	-1.53441978	2.9500003	0.13518036	1.0700037	4
-1.6860008	-0.038	0.883	1.1789997	2.7979999	0.6905882	0.8138054	0.6452944	-0.513	0.692	0.018	2.91120004	1.468320054	-1.396480446	3.0650005	0.095440001	1.05290294	4
-1.8000002	-2.757	2.7089999	1.1789997	2.5279999	0.9864503	0.7144088	0.9448332	-0.766	0.538	1.512	4.4429999	1.25293914	-1.92606016	3.1789999	0.097981564	0.73507553	4
-2.0299997	-1.149	1.301	1.1500006	2.299	0.7071236	0.8186269	0.8370217	-0.114	0.912	1.608	1.264	1.7939101	-1.3846802	3.1800003	0.104000438	1.03789811	4
-2.5289998	-2.136	0.115	0.7650998	1.4160001	0.4231105	0.6772577	0.7244644	-0.268	0.96	1.685	1.83799998	1.2111799	-2.0436187	3.2949996	0.138277279	1.76270827	4
-1.6470003	-1.8389999	1.761	1.999	2.8730001	0.5000416	0.8862431	1.0032867	-0.306	0.815	2.758	2.37400004	1.8370604	-1.8029199	3.6400003	0.133718346	1.53327727	4
-1.5709996	-1.6479999	1.6850001	2.2220001	2.758	0.6162406	0.7082301	0.9329981	-0.421	0.002	2.758	2.8720001	2.16763992	-1.62533878	3.7929997	0.134175089	1.3206823	4

Arquivo com todos os logs compilados





# Regressor: Metodologia

Escolha das variáveis

Otimização da topologia

*k-fold cross-validation*

Re-treino

Algoritmo *greedy*:

Comparar a rede de  $n$  variáveis com as  $n$  redes de  $n-1$  variáveis.

- A melhor rede de  $n-1$  foi melhor que a rede de  $n$ ? Repetir a operação.
- Caso contrário, parar por aqui.

**Resultado: guardamos as 5 features.**

# Regressor: Metodologia

Escolha das variáveis

Otimização da topologia

*k-fold cross-validation*

Re-treino

Busca extensiva:

Todas as combinações possíveis de topologias (número e tamanho das camadas escondidas) e variáveis foram geradas e testadas *overnight*.

**Resultado: uma camada escondida com 4 neurônios sigmoidais.**



# Regressor: Metodologia

Escolha das variáveis

Otimização da topologia

*k-fold cross-validation*

Re-treino

*10-fold cross validation:*

Treino

Treino

Treino

Treino

Treino

Treino

Treino

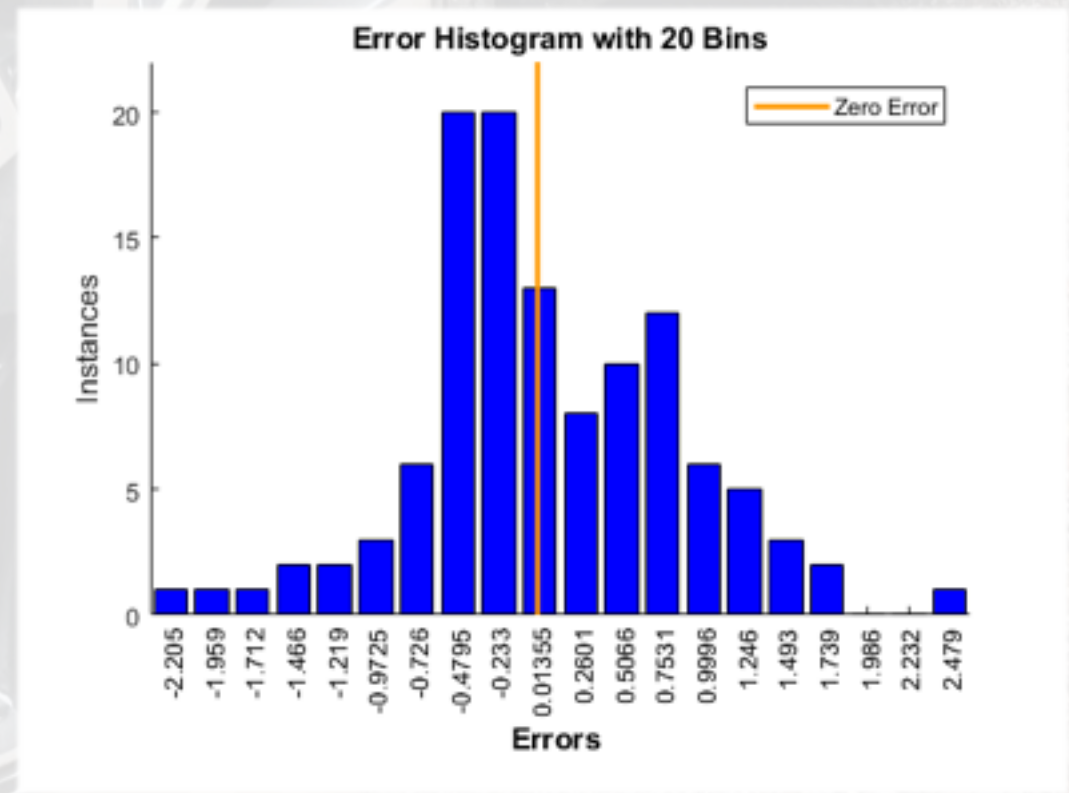
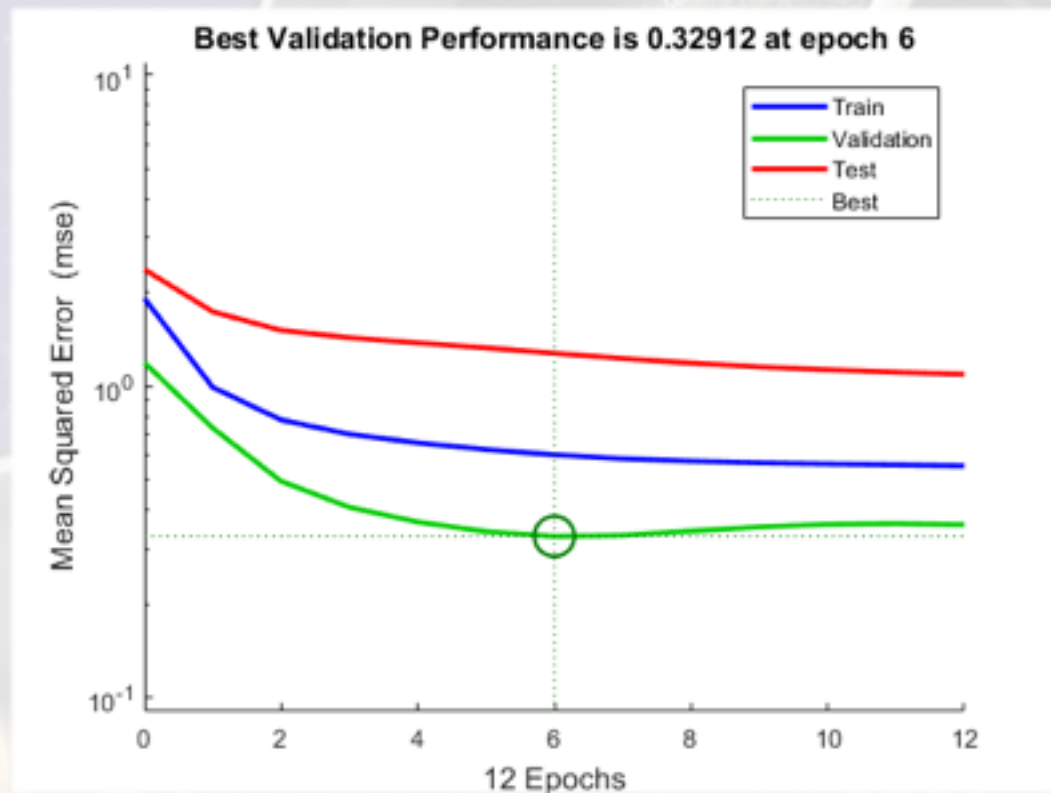
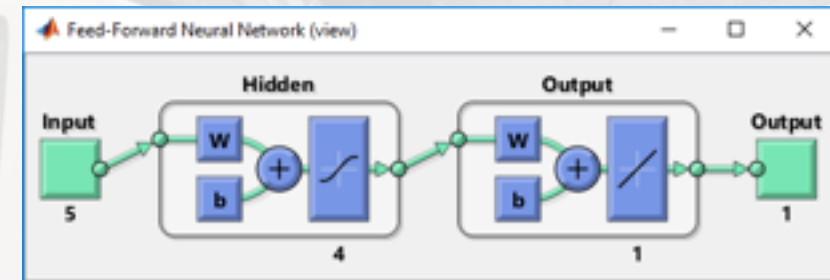
Treino

Valid.

Teste

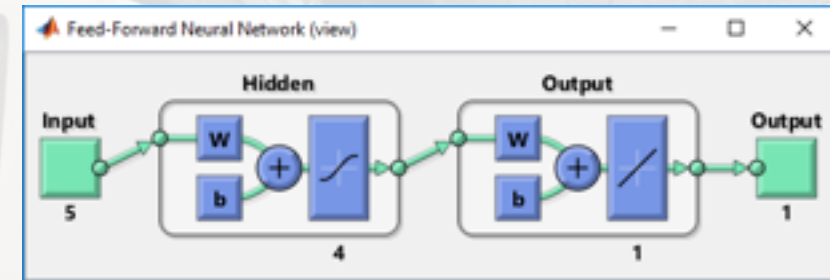
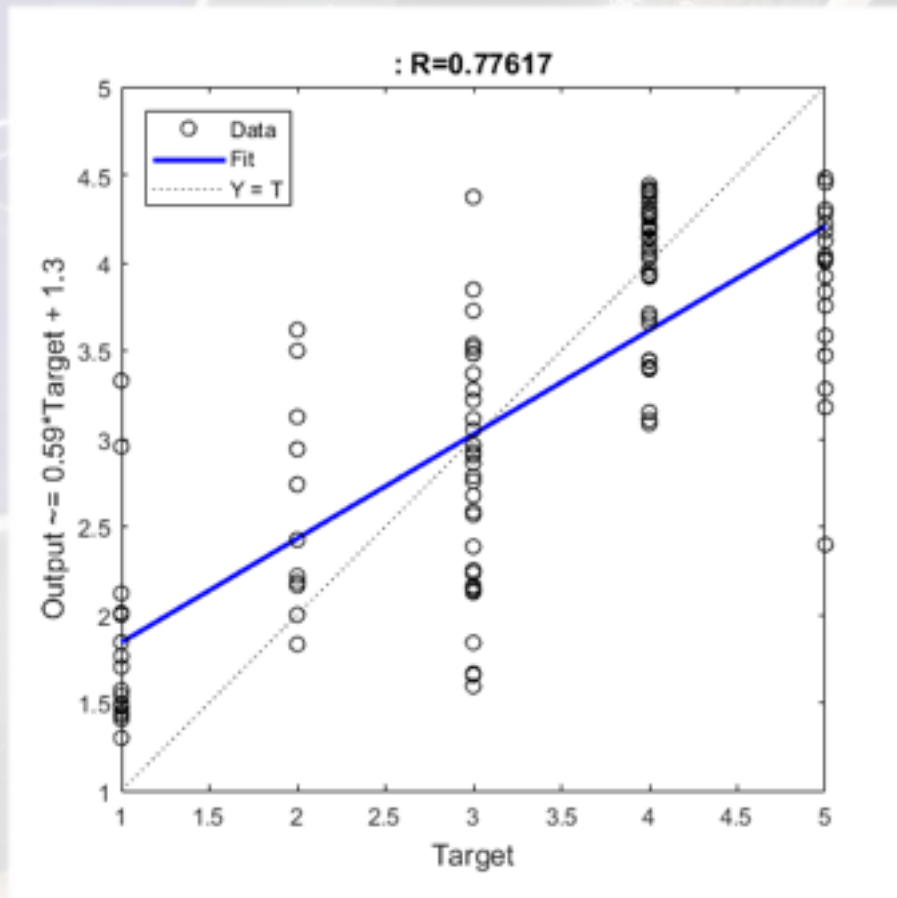
20 re-treinos para evitar mínimos locais

# Regressor: Resultados





# Regressor: Resultados



Indicator	Value
Mean Error	0.0671
Standard Deviation	0.8025
Mean Absolute Error	0.6257
Mean Squared Error	0.6429
Root Mean Squared Error	0.8018
Median	-0.0622
Maximum Positive Error	2.6020
Maximum Negative Error	-2.3284



# Regressor: Prova de Conceito



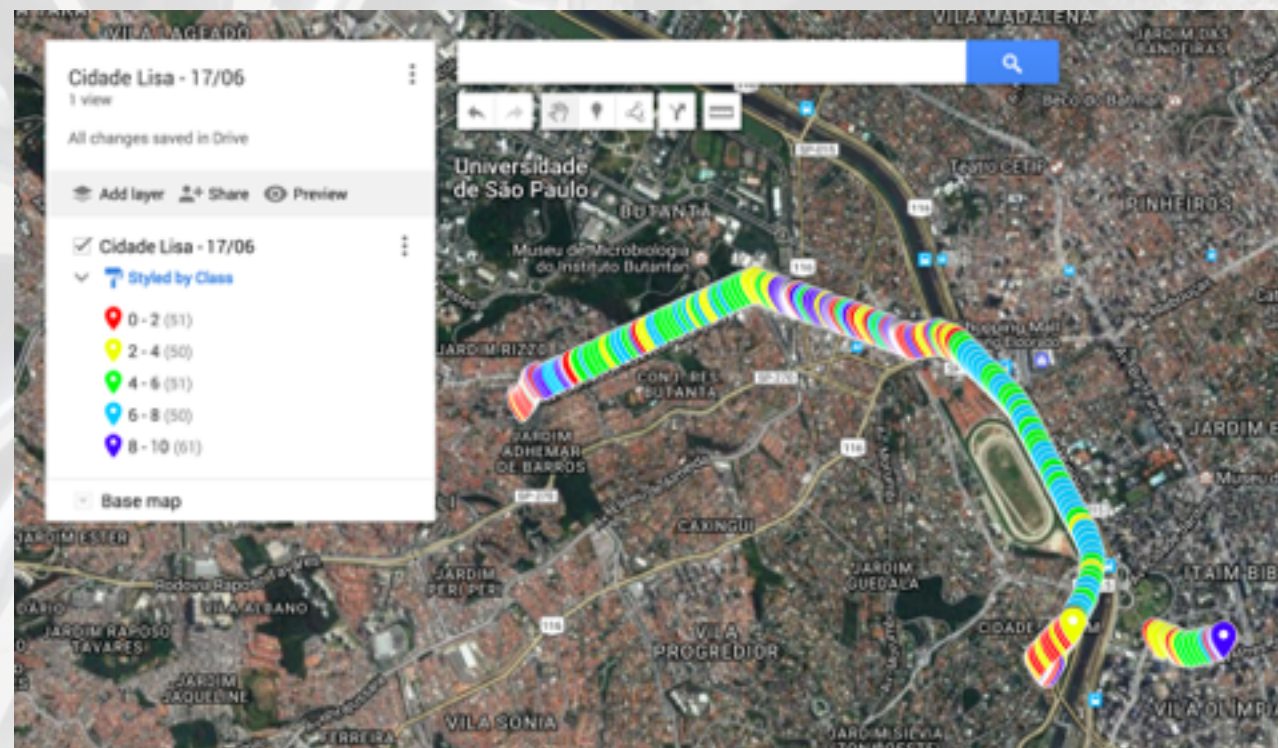
[https://youtu.be/dC\\_tfyN0lp4](https://youtu.be/dC_tfyN0lp4)



# Regressor: Pós-Processamento de Dados

Time	Latitude	Longitude	Class	-T
16:00:07	-23.576443333333334	-46.730818333333334	6.670848802612243	
16:00:10	-23.576463333333333	-46.730761666666666	2.506907840689695	
16:00:13	-23.57642	-46.73065	8.717083007626286	
16:00:16	-23.576361666666667	-46.730474999999999	2.000417211374395	
16:00:19	-23.576249999999998	-46.730321666666667	2.039868149866655	
16:00:22	-23.57609	-46.730216666666667	7.819218864936794	
16:00:25	-23.575916666666664	-46.73015	2.048814660980271	
16:00:28	-23.575705000000003	-46.730098333333334	2.0044471170424294	
16:00:32	-23.575513333333333	-46.730046666666674	6.519351837180351	
16:00:35	-23.575305000000004	-46.729973333333333	5.089785699837046	
16:00:38	-23.575188333333337	-46.729911666666667	4.701097129842713	
16:00:41	-23.57509	-46.729876666666666	6.474466593684389	
16:00:44	-23.575073333333333	-46.729878333333333	6.400082338435934	
16:00:47	-23.575073333333333	-46.729878333333333	8.717083007626286	
16:00:50	-23.575073333333333	-46.729878333333333	8.717083007626286	
16:01:36	-23.575055	-46.72999	8.71563442217452	
16:01:39	-23.57505	-46.729991666666667	8.717083007626286	
16:01:42	-23.57505	-46.729991666666667	8.717083007626286	
16:02:00	-23.574994999999998	-46.729936666666666	5.414752701813974	
16:02:03	-23.575016666666667	-46.729813333333334	9.957695099722656	
16:02:06	-23.575041666666667	-46.729761666666666	7.957299865241671	
16:02:09	-23.575048333333333	-46.729741666666666	8.717083007626286	
16:02:12	-23.575048333333333	-46.729741666666666	8.717083007626286	
16:02:25	-23.57506	-46.729641666666667	8.717083007626286	
16:02:28	-23.575071666666666	-46.729625000000006	8.717083007626286	
16:02:31	-23.575146666666667	-46.729575000000004	4.977347054346976	
16:02:34	-23.575296666666667	-46.729546666666664	8.12357747692614	
16:02:37	-23.575429999999997	-46.729581666666667	6.902104480453204	
16:02:40	-23.575588333333332	-46.729635000000001	2.0229601743972045	
16:02:43	-23.57578	-46.729691666666667	3.6445495332235778	
16:02:46	-23.576008333333334	-46.729756666666666	5.689440978722795	
16:02:49	-23.576251666666668	-46.729843333333335	6.2685682655168575	
16:02:52	-23.576486666666664	-46.729943333333333	5.344399714113996	
16:02:55	-23.576729999999998	-46.730066666666666	5.973421138545221	
16:02:58	-23.576976666666663	-46.73024	5.409925430973388	

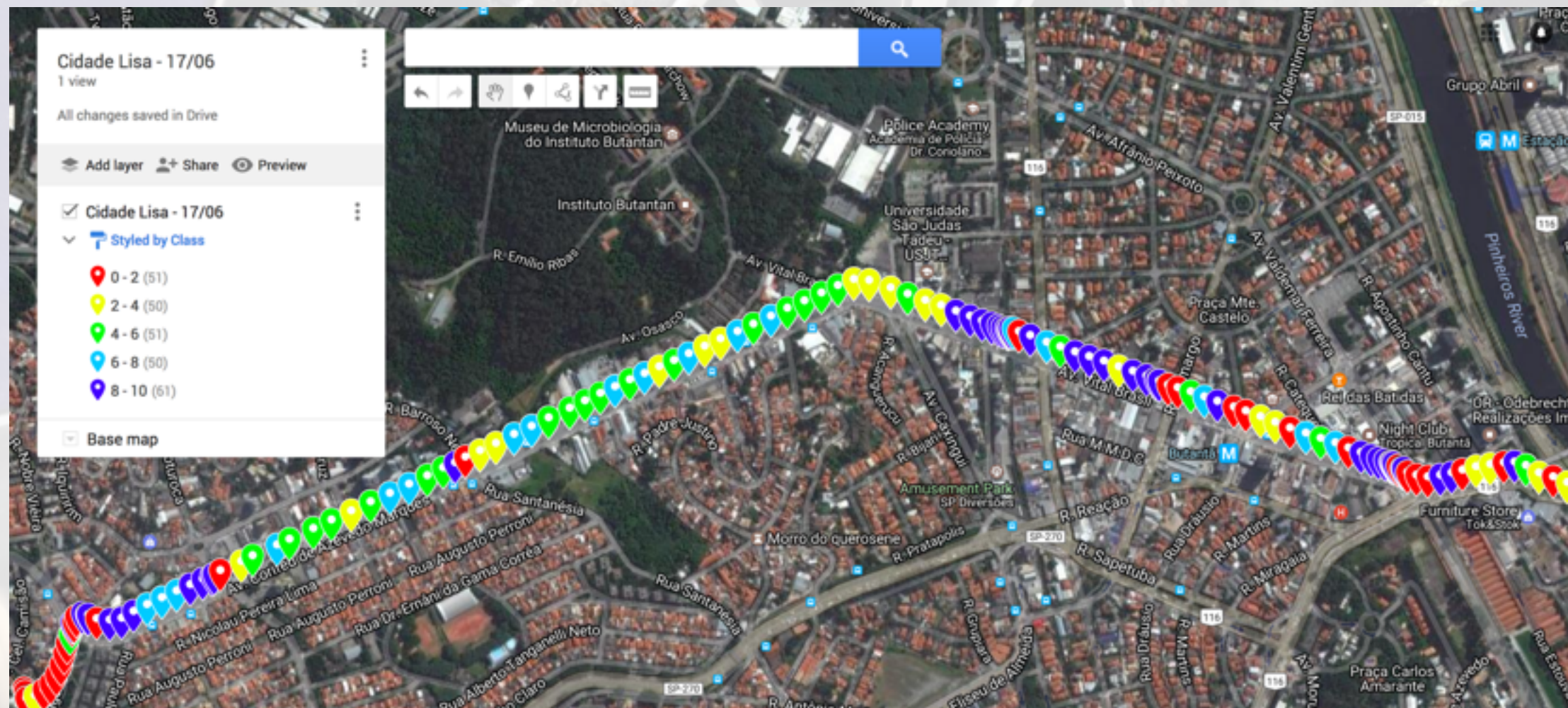
Arquivo importado no Google Maps



Arquivo salvo ao final da rota

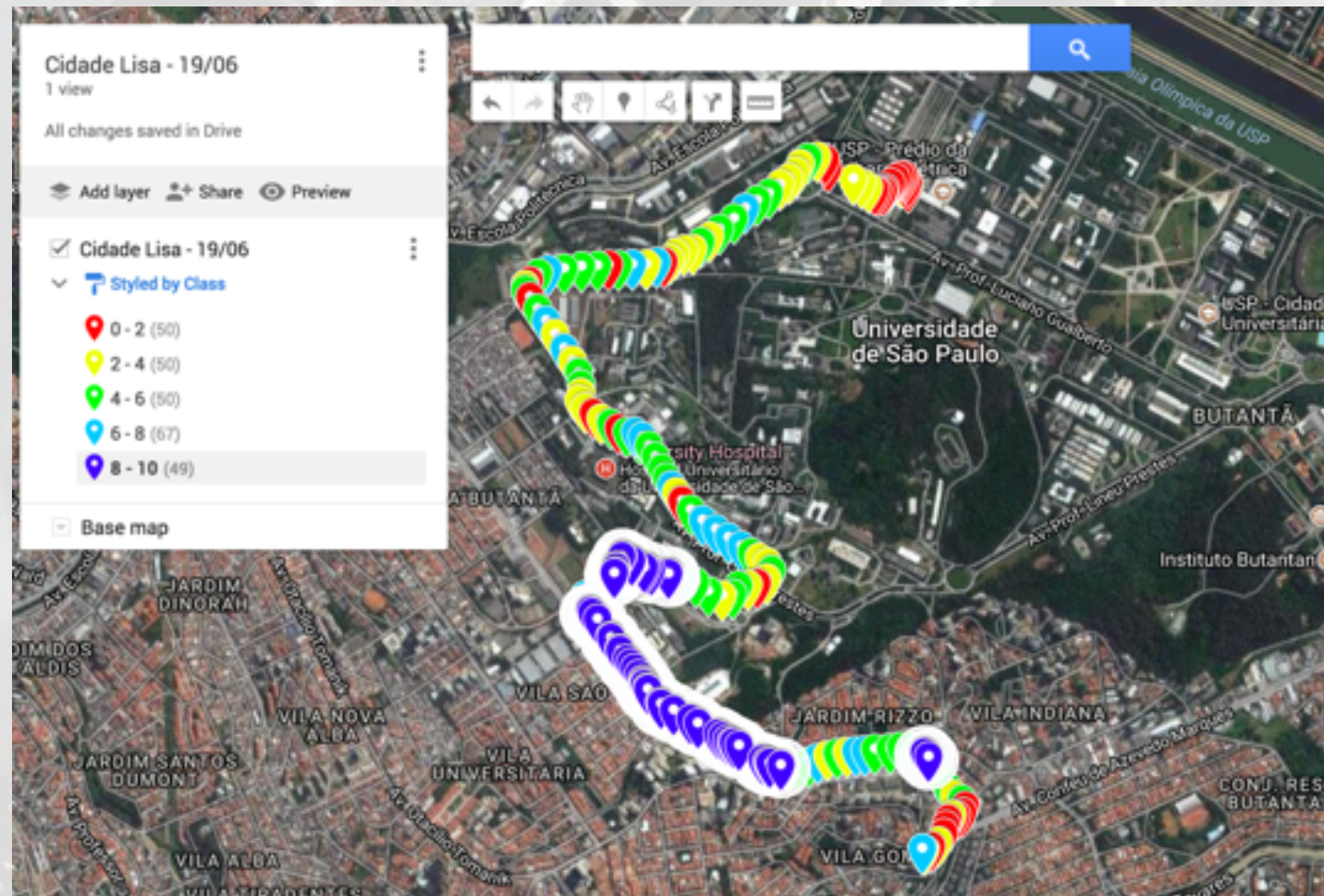


# Regressor: Pós-Processamento de Dados



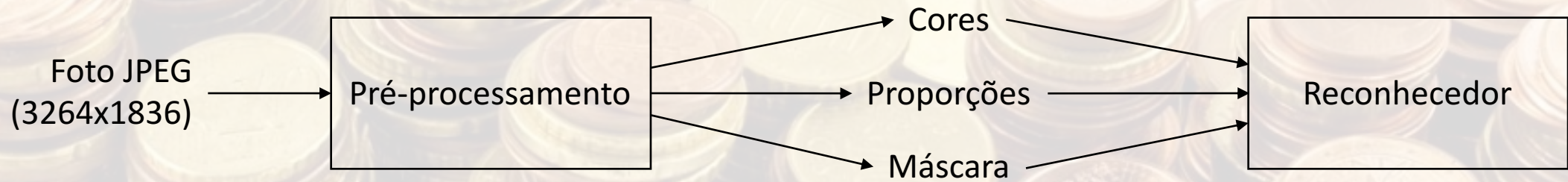


# Regressor: Pós-Processamento de Dados





# Reconhecedor: Identificação de moedas

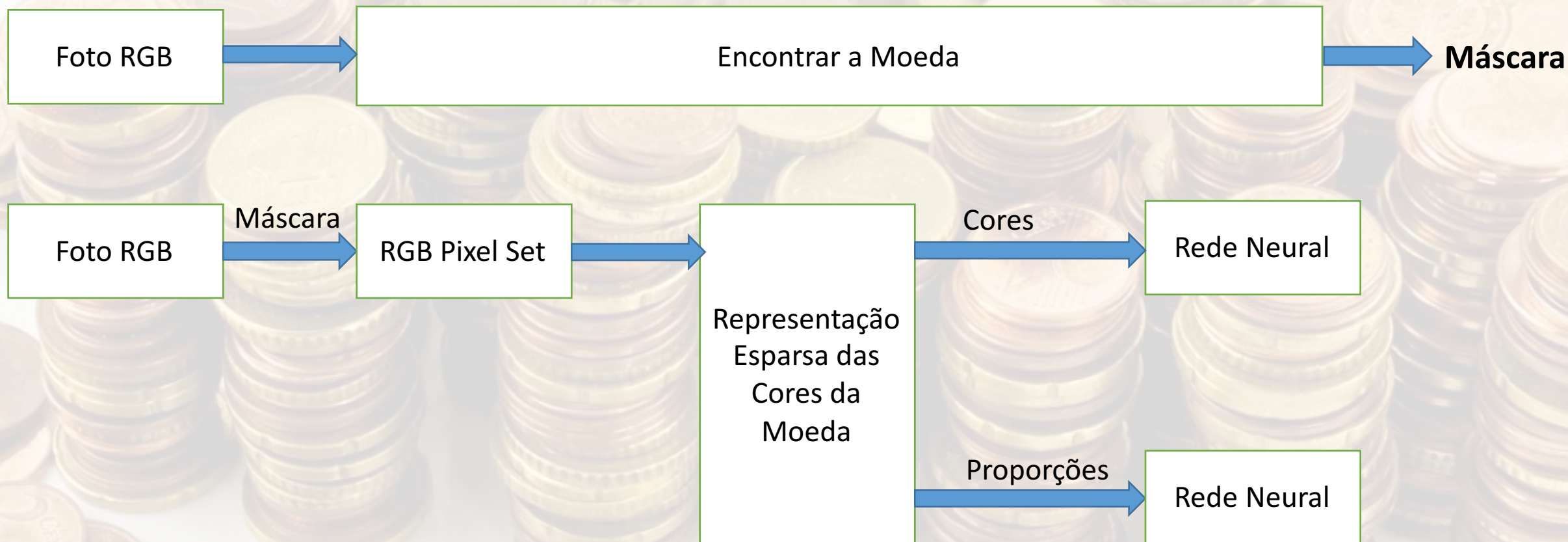


Saída: Valor nominal da moeda

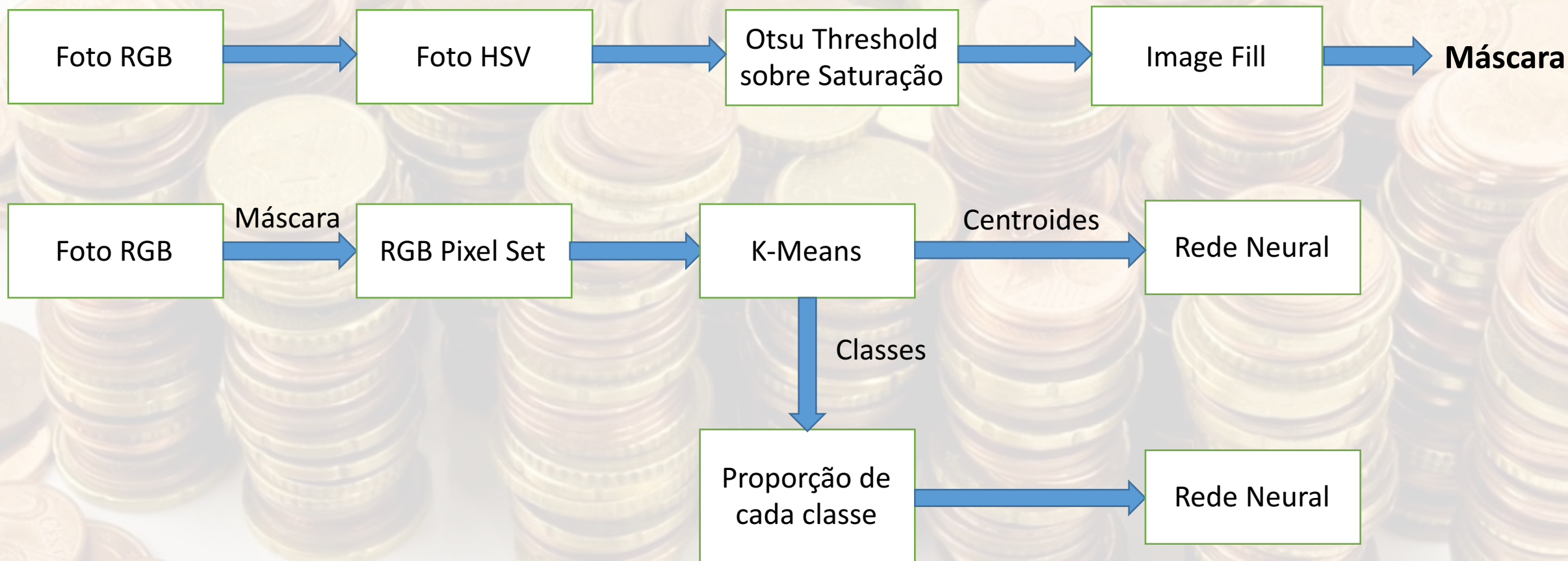




# Reconhecedor: Pré-processamento

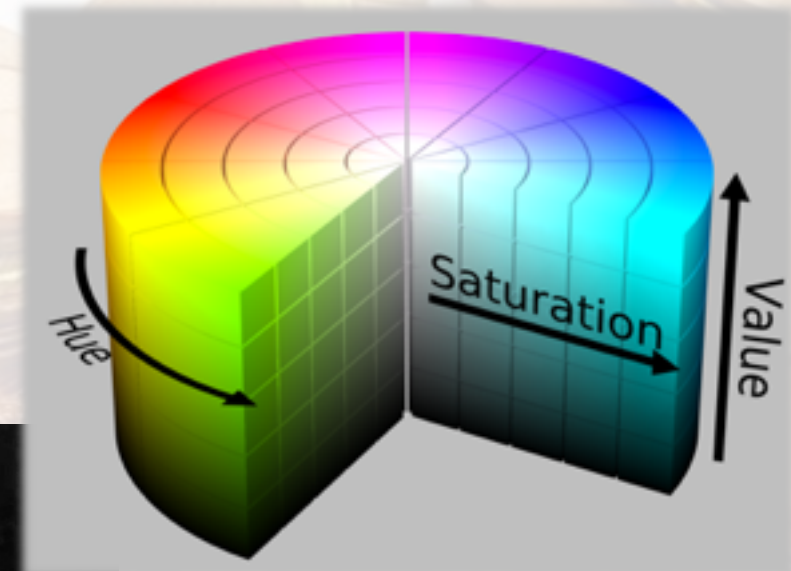
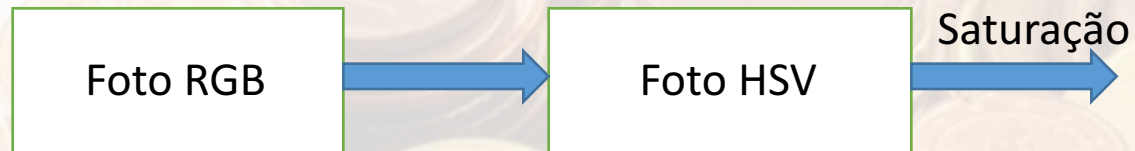


# Reconhecedor: Pré-processamento





# Reconhecedor: Pré-processamento



# Reconhecedor: Pré-processamento

Foto HSV

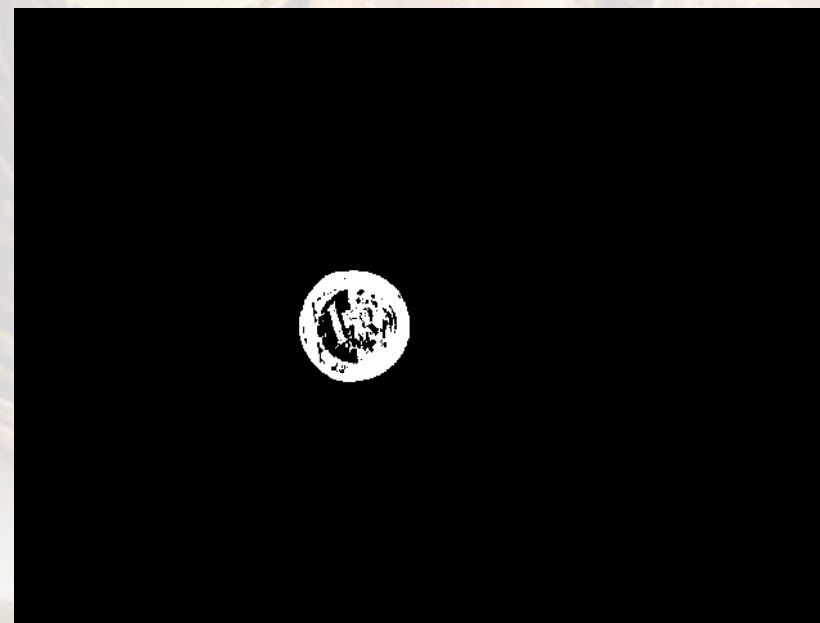
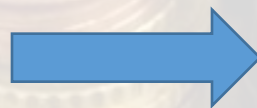
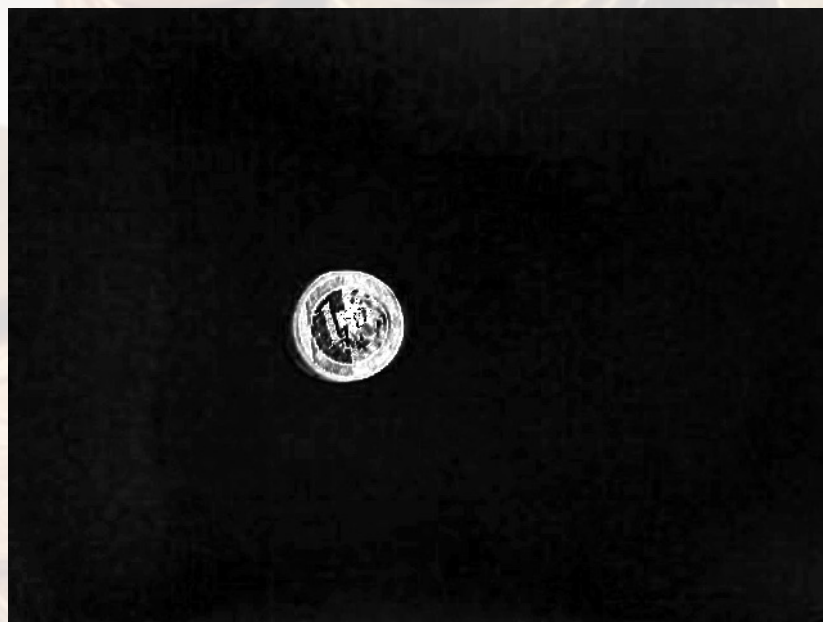
Otsu Threshold  
sobre Saturação

Encontra o threshold  $T$  que minimiza a variância intra-classes

$$T = \arg \min_T \sigma_b^2(T)$$

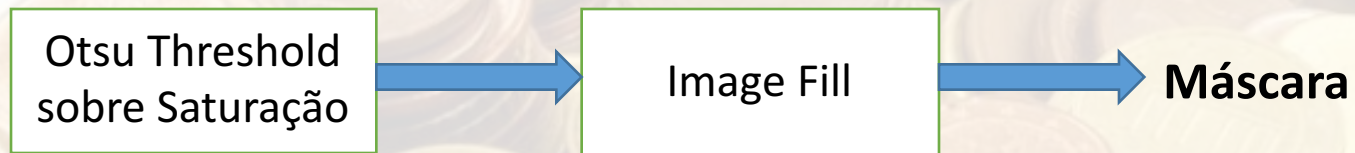
$$\sigma_b^2(T) = p(X \leq T)(\mu_0(T) - \mu)^2 + p(X > T)(\mu_1(T) - \mu)^2$$

$$\mu = E[X]; \mu_0(T) = E[X|X \leq T]; \mu_1(T) = E[X|X > T]$$





# Reconhecedor: Pré-processamento



**Preenche o interior de regiões fechadas!**  
**Mais de uma região conexa: Escolhemos a maior!**



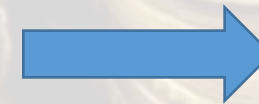
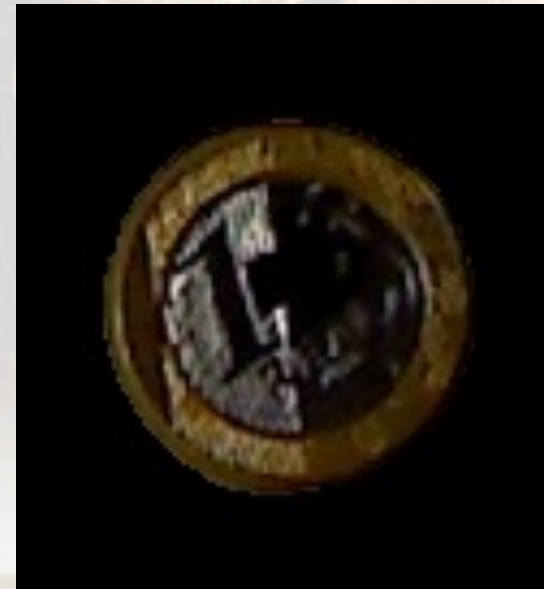
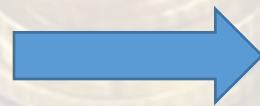


# Reconhecedor: Pré-processamento

Foto RGB

Máscara

RGB Pixel Set



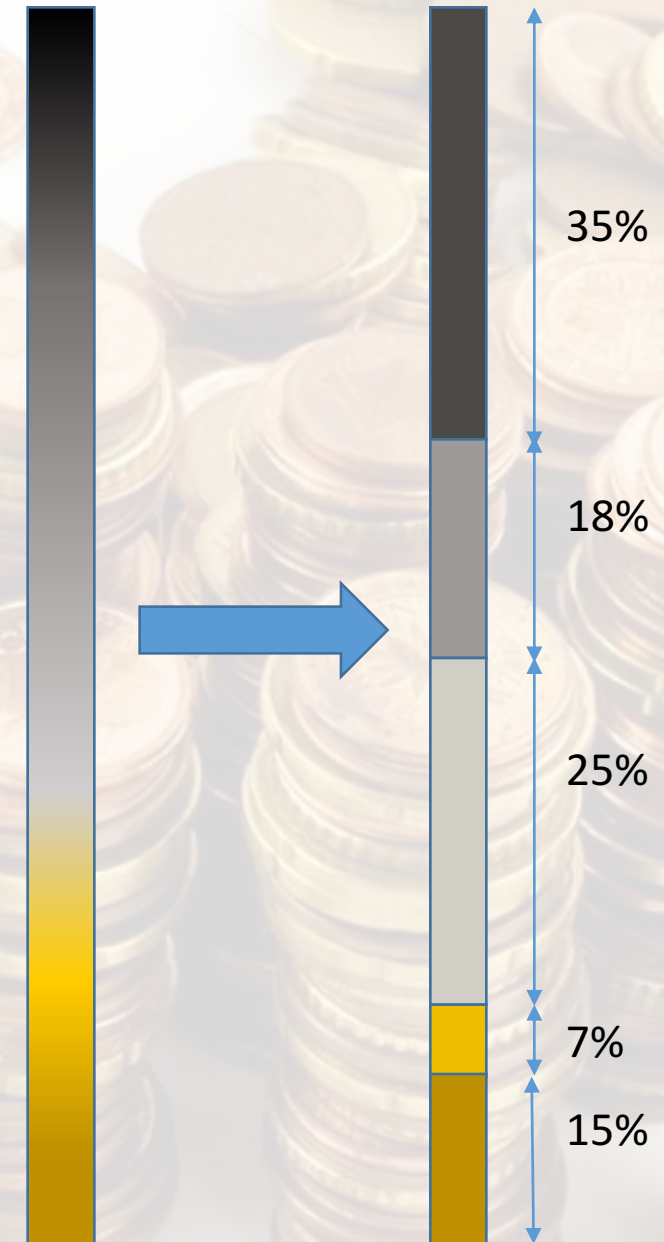


# Reconhecedor: Pré-processamento

RGB Pixel Set

K-Means

Centroides e  
Proporções



5 cores principais



# K-Means

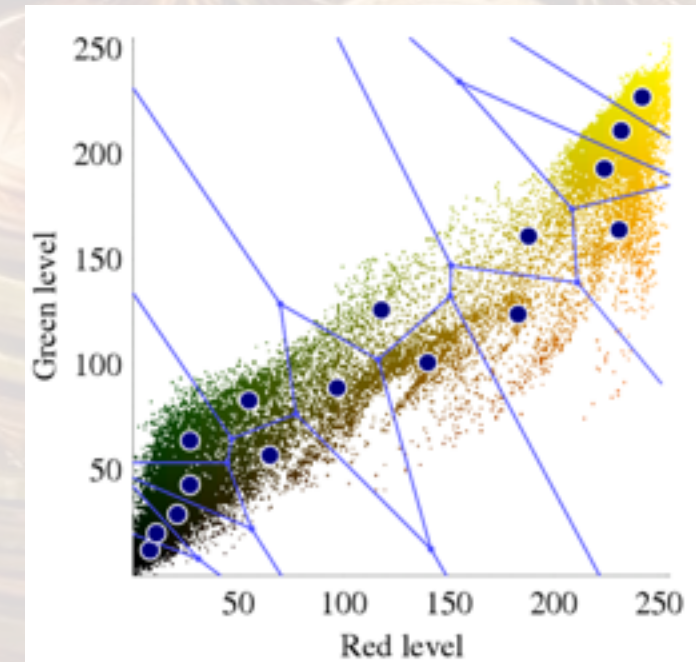
- Baixa complexidade:  $\approx \mathcal{O}(n)$
- Fronteiras de separação lineares
- Usuário escolhe o número de clusters K



Inicie os K centroides aleatoriamente.

## A cada iteração:

1. Rotule cada ponto com a classe do centroide mais próximo.
2. Os novos centroides são os centroides de cada classe.



K = 16

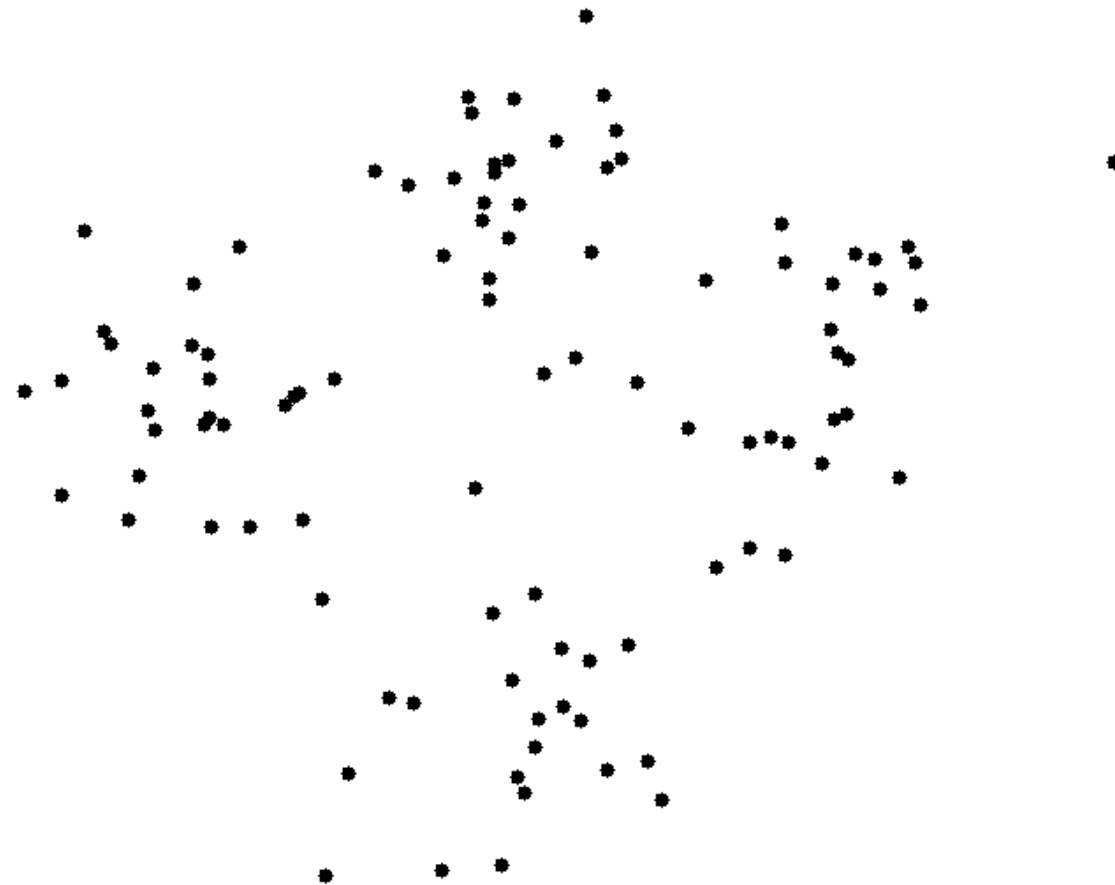


# K-Means





# K-Means





# Reconhecedor: Pré-processamento

Foto RGB



Saturação



Otsu Threshold

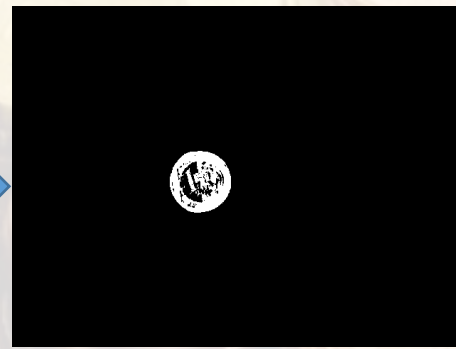
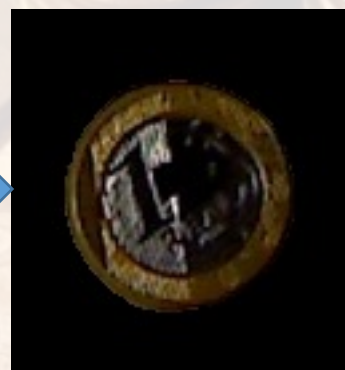
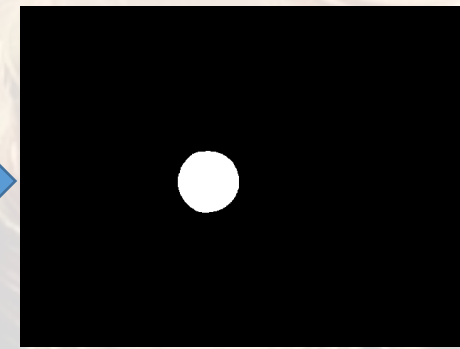
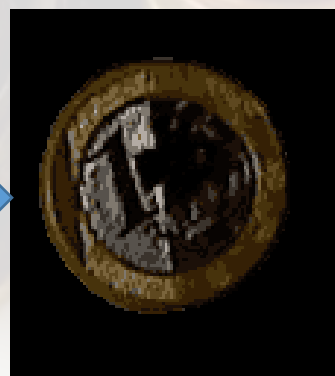


Image Fill



Aplicação da Máscara



K-Means  
K=5

Centroides e  
Proporções

Rede Neural



# Reconhecedor: Metodologia

Resorteio do kmeans

Otimização da topologia

*k-fold cross-validation*

Re-treino



# Reconhecedor: Metodologia

Resorteio do kmeans

Otimização da topologia

*k-fold cross-validation*

Re-treino

Busca extensiva:

Todas as combinações possíveis de topologias (número e tamanho das camadas escondidas) e variáveis foram geradas e testadas *overnight*.

**Resultado: duas camadas escondidas com 10 e 7 neurônios sigmoidais.**



# Reconhecedor: Metodologia

Resorteio do kmeans

Otimização da topologia

*k-fold cross-validation*

Re-treino

*10-fold cross validation:*

Treino

Treino

Treino

Treino

Treino

Treino

Treino

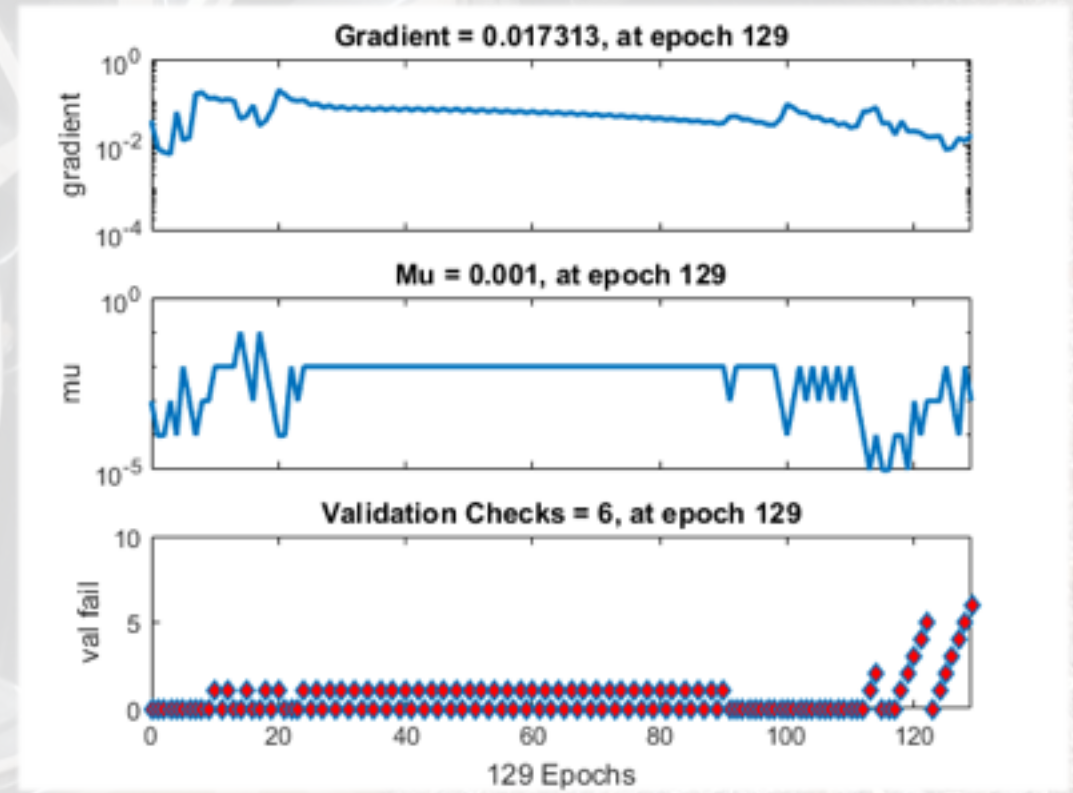
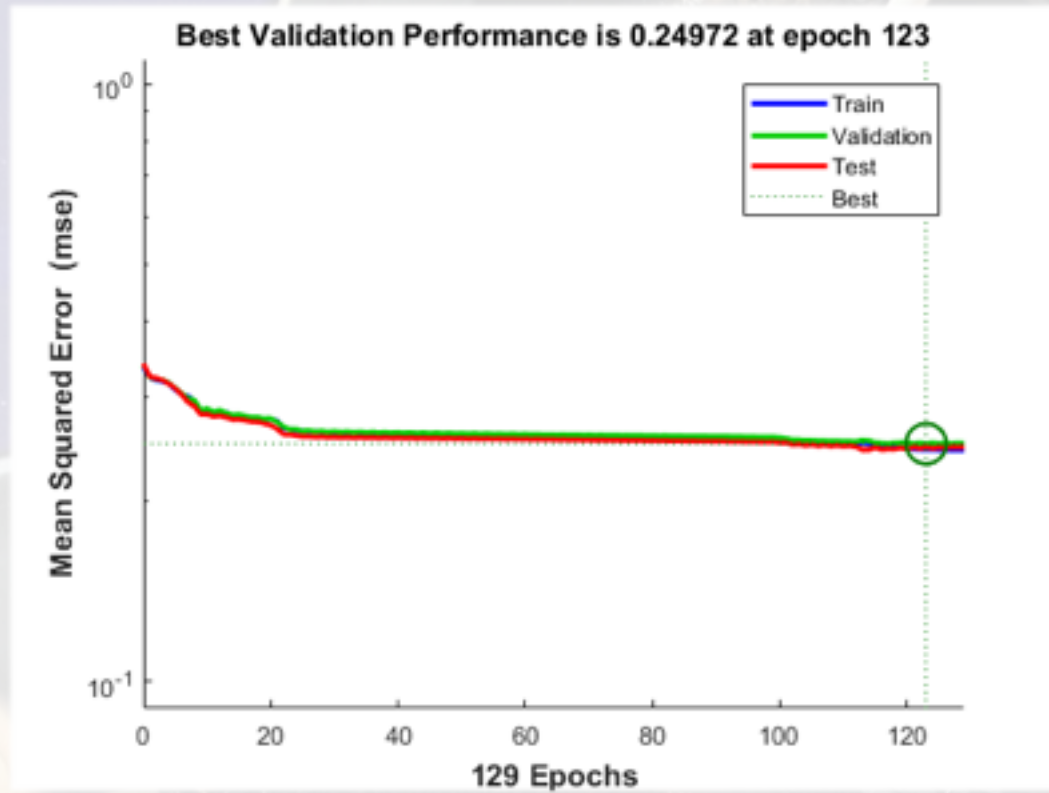
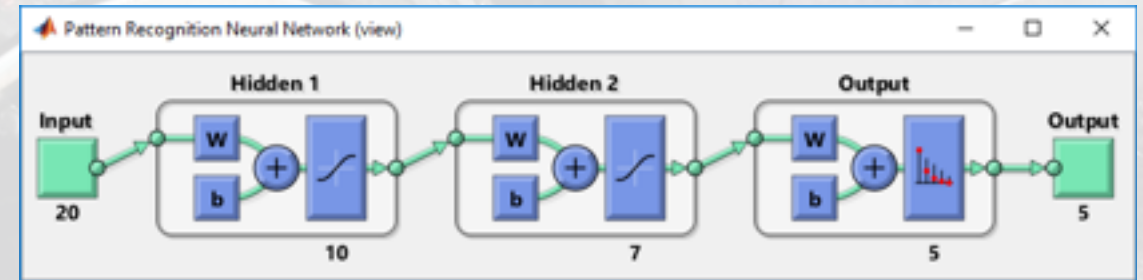
Treino

Valid.

Teste

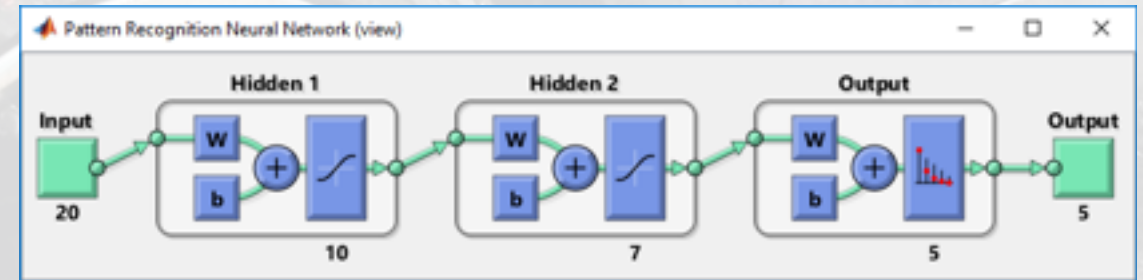
10 re-treinos para evitar mínimos locais

# Reconhecedor: Resultados



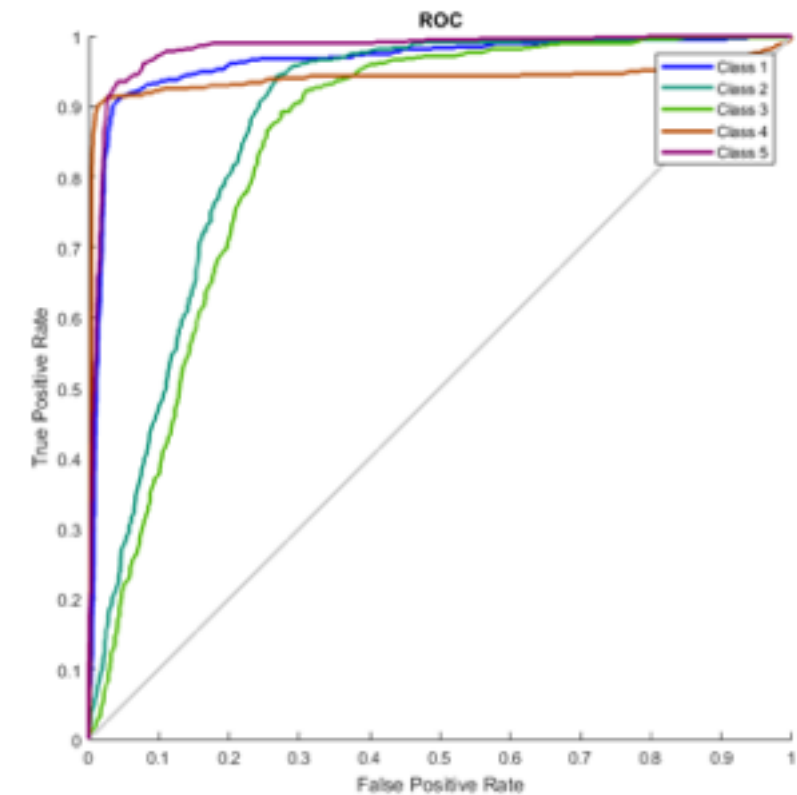


# Reconhecedor: Resultados



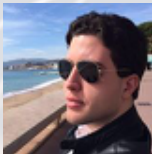
**Confusion Matrix**

Output Class \ Target Class	1	2	3	4	5	
1	544 17.8%	34 1.1%	28 0.9%	34 1.1%	2 0.1%	84.7% 15.3%
2	22 0.7%	431 14.1%	363 11.9%	2 0.1%	12 0.4%	51.9% 48.1%
3	23 0.8%	120 3.9%	160 5.2%	5 0.2%	24 0.8%	48.2% 51.8%
4	6 0.2%	6 0.2%	9 0.3%	576 18.8%	9 0.3%	95.0% 5.0%
5	5 0.2%	12 0.4%	45 1.5%	25 0.8%	562 18.4%	86.6% 13.4%
	90.7% 9.3%	71.5% 28.5%	26.4% 73.6%	89.7% 10.3%	92.3% 7.7%	74.3% 25.7%

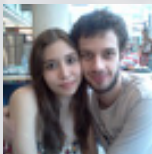


# MUITO OBRIGADO! PERGUNTAS?

## Regressor de Qualidade das Vias

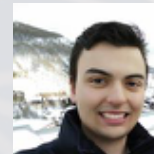


Carlos Grivol

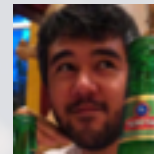


Carlos Prete

## Reconhecedor de Moedas



Gabriel Crabbé



Tiago Amano



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- [9] MOHAN, P.; PADMANABHAN, V. N.; RAMJEE, R.; MURPHY, M. Nericell: Rich Monitoring of Road and Traffic Conditions using Mobile Smartphones. *Microsoft Research India*, Bangalore. 2008.
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# Reconhecedor: Referências

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- [3] Arthur; Abhishek Bhowmick (2009). *A theoretical analysis of Lloyd's algorithm for k-means clustering* (Tese)
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- [6] Digital Image Processing (3<sup>rd</sup> Edition) – Rafael C. Gonzalez, Richard E. Woods - Pearson