Outline for today

1. Classification Metrics
2. Image Features
3. Data Set
4. Submission System

Classification Metrics

- Numbers which tell how well a classification problem is solved
- Example: Detect lung cancer from CT images
- Labels:
  - N: no cancer
  - P: cancer
- Build a classifier, than evaluate it on known cases

Different possible outcomes

Outcome	Predicted Label	True Label	
true positive (TP)	P	P	
false positive (FP)	P	N	← Type I error
false negative (FN)	N	P	
true negative (TN)	N	N	← Type II error

Accuracy

- Accuracy: Proportion of true results among all cases

$$\frac{TP + TN}{TP + FP + TN + FN}$$

- Problematic in unbalanced dataset
  - E.g. # Positives < # Negatives

$$\frac{\cancel{TP} + TN}{\cancel{TP} + FP + TN + \cancel{FN}}$$

  - Easy to always predict „Negative“

$$\frac{\cancel{TP} + TN}{\cancel{TP} + \cancel{FP} + TN + \cancel{FN}} \approx 1$$

Sensitivity and Specificity

- Sensitivity or true positive rate (TPR)
  - Proportion of true positive among all positives

$$\frac{TP}{TP+FN}$$

- Specificity or true negative rate (TNR)
  - Proportion of true positive among all positives

$$\frac{TN}{TN+FP}$$

Sensitivity and Specificity

- False positive rate (FPR)

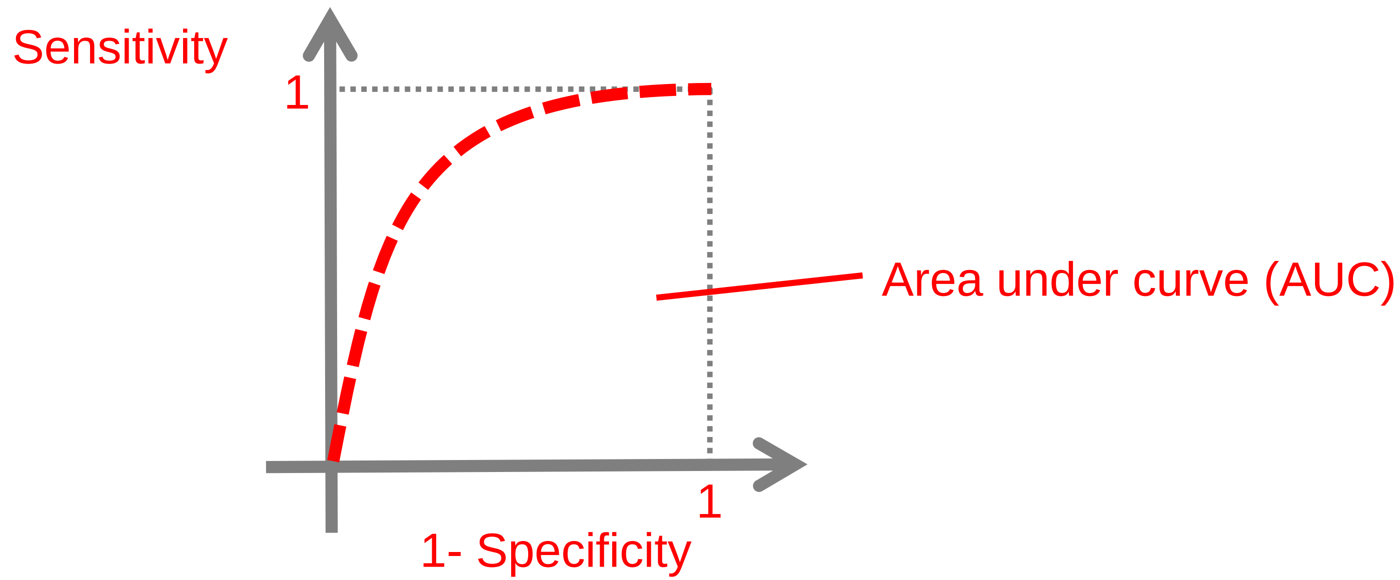
$$\frac{FP}{TN+FP} = \frac{TN+FP}{TN+FP} - \frac{TN}{TN+FP} = 1 - \frac{TN}{TN+FP} = 1 - TNR$$

- False negative rate (FNR)

$$\frac{FN}{TP+FN} = \frac{TP+FN}{TP+FN} - \frac{TP}{TP+FN} = 1 - \frac{TP}{TP+FN} = 1 - TPR$$

Receiver Operating Characteristic (ROC)

- Balance Sensitivity and Specificity
- Plots TPR (Sensitivity) against FPR (1-Specificity)
- Can also be used to find thresholds



Recall, Precision, F1 score

- Recall = TPR = Sensitivity

$$\frac{TP}{TP + FN}$$

- Precision

$$\frac{TP}{TP + FP}$$

- F1 Score (harmonic mean of recall and precision)

$$F_1 = 2\,\frac{Precision * Recall}{Precision + Recall}$$

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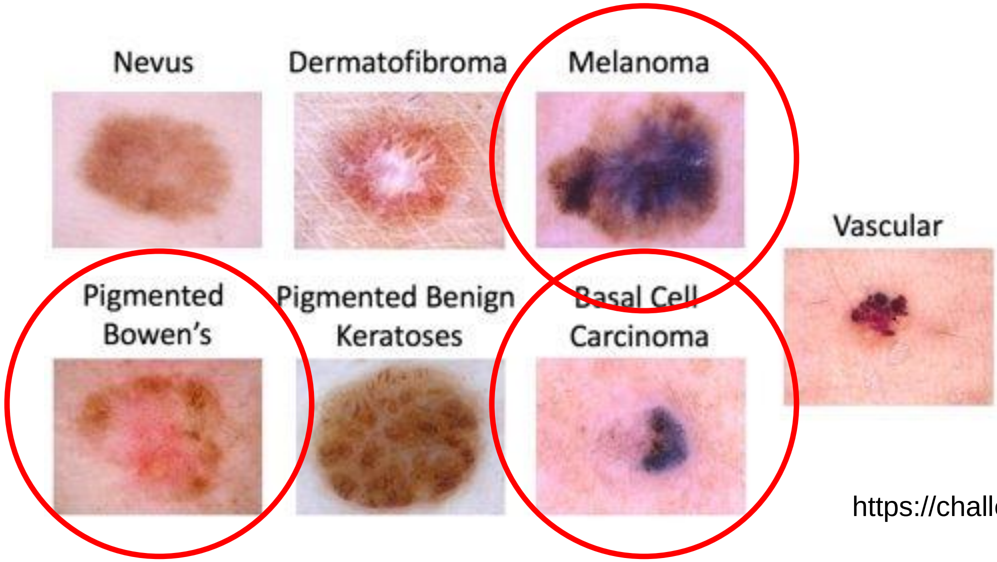
Image Features

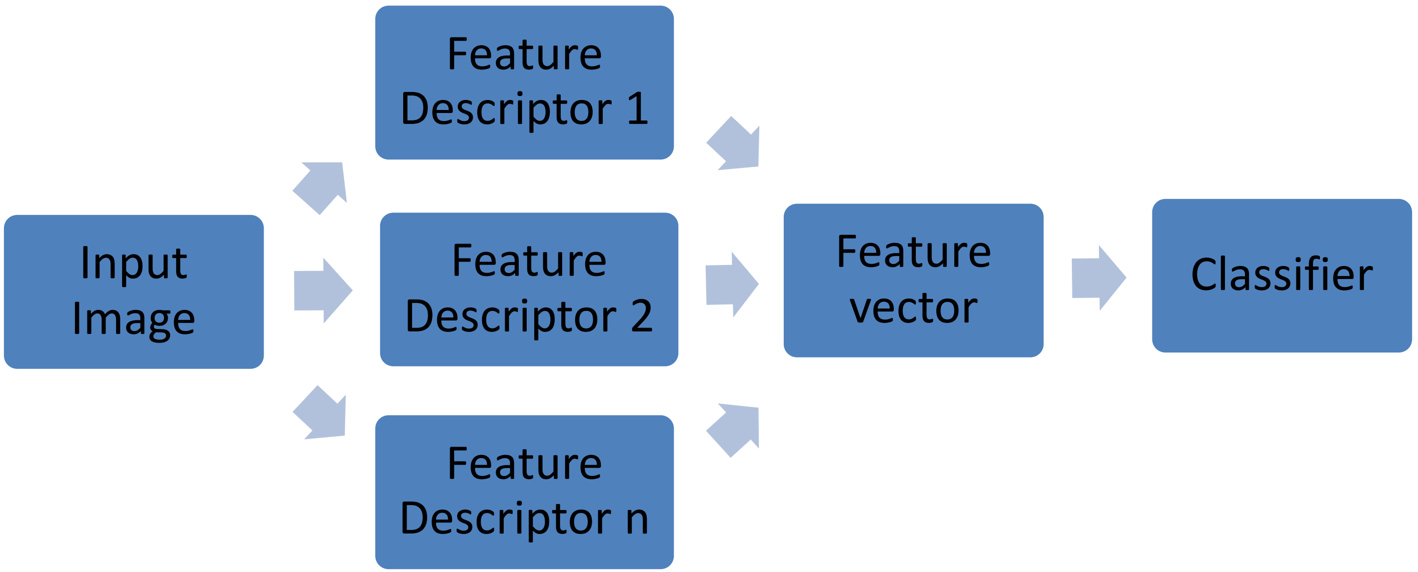
- Goal: Extract information as a list of numbers from images



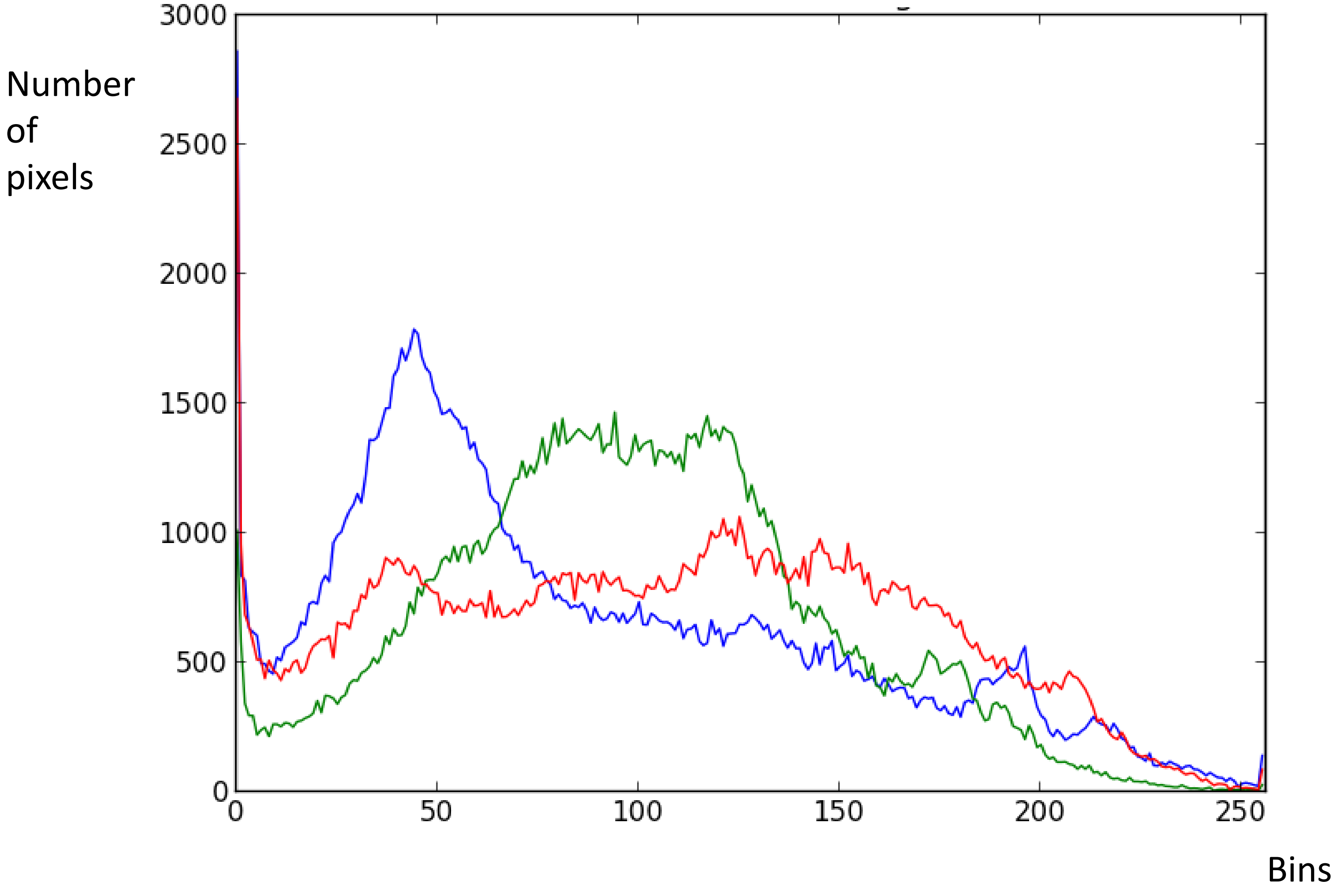
https://challenge2018.isic-archive.com/task3/

- What properties can be used to distiguish benign from malignant?
  - Color
  - Shape
  - Texture

Image Features



Color Histograms



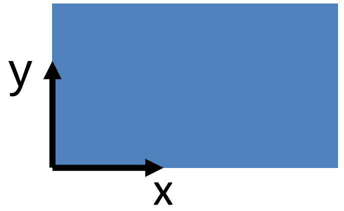
Moments

- General spatial moments:

$$M_{pq} = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} x^p \, y^q f(x,y) dxdy$$

- Analogy in Mechanics:

$$\bar{x} = \frac{M_{10}}{M_{00}} = \frac{\int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} x^1 \, \rho(x,y) dxdy}{\int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \rho(x,y) dxdy}$$



- Higher order moments capture distribution of „mass“

Hue Moments

- Central moments:

$$\mu_{pq} = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} (x - \bar{x})^p \, (y - \bar{y})^q f(x, y) dx dy$$

- For digital images:

$$\mu_{pq} = \sum_x \sum_y (x - \bar{x})^p (y - \bar{y})^q$$

- Seven Hue moments [1] are calculated from combinations of central moments

e.g. $(\mu_{20} - \mu_{02})^2 + {\mu_{11}}^2$

[1] M. K. Hu, "Visual Pattern Recognition by Moment Invariants", IRE Trans. Info. Theory, vol. IT-8, pp.179–187, 1962

Hue Moments (2)

- Hue moments are invaraint to:
  - Image scale
  - Translations
  - Rotations
  - Reflections (partially)

Other feature descriptors

- Texture, e.g. Haarlick
- Histogram of Oriented Gradients (HOG)
- Make sure different features are on the same scale, normalize!
- Search for more feature descriptors and try out different combinations

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Data Set

- Link to dataset:

  https://challenge2018.isic-archive.com/task3/

- 10k training images with labels, 1.5k test images without labels
- Validation split of 2.5k images in Stud.IP
- Two tasks: Multiclass and binary classification

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Submission System

- Link to website:

  https://cgi.tu-harburg.de/~c00e1fn1/

- Groups