

# Gradient Boosting

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# Why Gradient Boosting?

## Machine Learning Challenge Winning Solutions

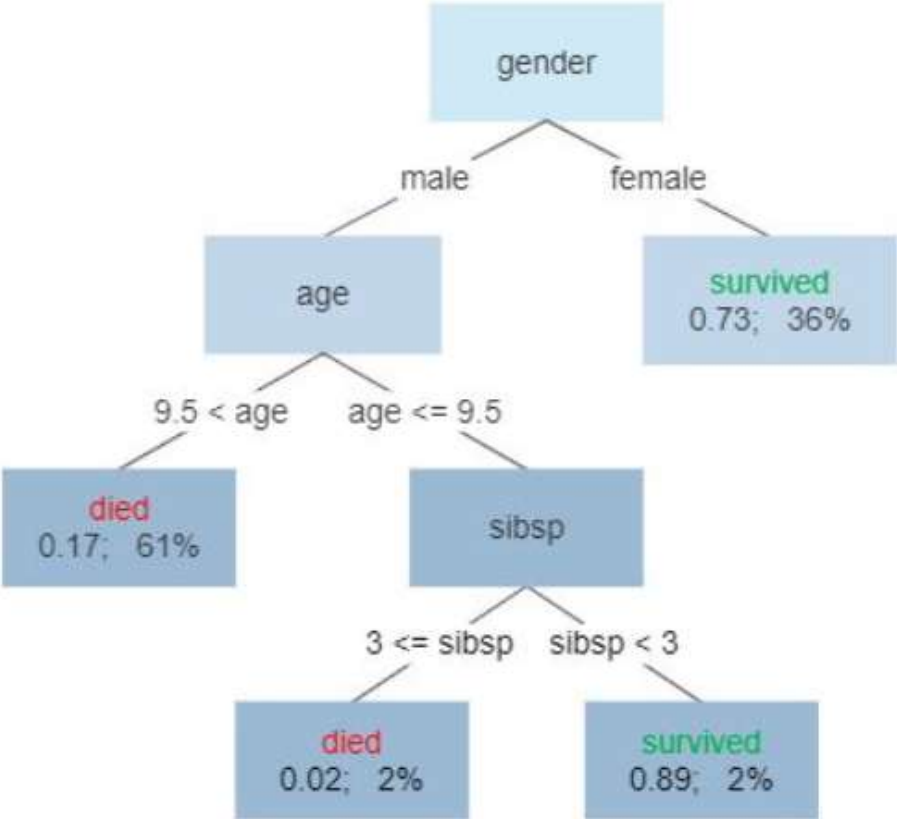
LightGBM is used in many winning solutions, but this table is updated very infrequently.

Place	Competition	Solution	Date
1st	<a href="#">M5 Forecasting - Uncertainty</a>	<a href="#">link</a>	2020.7
3rd	<a href="#">M5 Forecasting - Uncertainty</a>	<a href="#">link</a>	2020.7
3rd	<a href="#">ALASKA2 Image Steganalysis</a>	<a href="#">link</a>	2020.7
1st	<a href="#">M5 Forecasting - Accuracy</a>	<a href="#">link</a>	2020.6
2nd	<a href="#">COVID19 Global Forecasting (Week 5)</a>	<a href="#">link</a>	2020.5
3rd	<a href="#">COVID19 Global Forecasting (Week 5)</a>	<a href="#">link</a>	2020.5
1st	<a href="#">COVID19 Global Forecasting (Week 4)</a>	<a href="#">link</a>	2020.5
2nd	<a href="#">COVID19 Global Forecasting (Week 4)</a>	<a href="#">link</a>	2020.5
2nd	<a href="#">2019 Data Science Bowl</a>	<a href="#">link</a>	2020.1
3rd	<a href="#">RSNA Intracranial Hemorrhage Detection</a>	<a href="#">link</a>	2019.11
1st	<a href="#">IEEE-CIS Fraud Detection</a>	<a href="#">link</a>	2019.10
2nd	<a href="#">IEEE-CIS Fraud Detection</a>	<a href="#">link</a>	2019.10
2nd	<a href="#">Kuzushiji Recognition</a>	<a href="#">link</a>	2019.10
1st	<a href="#">Los Alamos National Laboratory Earthquake Prediction</a>	<a href="#">link</a>	2019.6
3rd	<a href="#">Los Alamos National Laboratory Earthquake Prediction</a>	<a href="#">link</a>	2019.6
1st	<a href="#">Santander Customer Transaction Prediction</a>	<a href="#">link</a>	2019.4
2nd	<a href="#">Santander Customer Transaction Prediction</a>	<a href="#">link</a>	2019.4
3rd	<a href="#">Santander Customer Transaction Prediction</a>	<a href="#">link</a>	2019.4
2nd	<a href="#">PetFinder.my Adoption Prediction</a>	<a href="#">link</a>	2019.4
1st	<a href="#">Google Analytics Customer Revenue Prediction</a>	<a href="#">link</a>	2019.3
1st	<a href="#">VSB Power Line Fault Detection</a>	<a href="#">link</a>	2019.3
5th	<a href="#">Elo Merchant Category Recommendation</a>	<a href="#">link</a>	2019.3

<https://github.com/microsoft/LightGBM/blob/master/examples/README.md#machine-learning-challenge-winning-solutions>

# Decision Trees

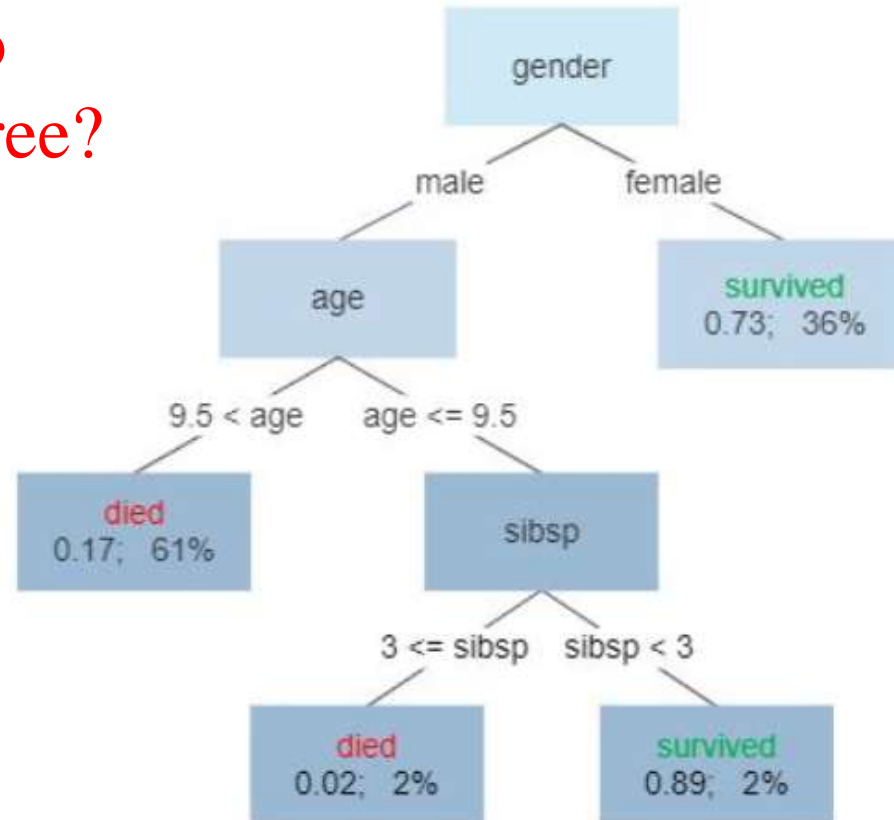
Survival of passengers on the Titanic



# Decision Trees

Given a dataset, how to find the best decision tree?

Survival of passengers on the Titanic



# Tree Split Criteria

- Estimate of Positive Correctness

$$E_P = TP - FP$$

- Gini impurity

$$I_G(p) = \sum_{i=1}^J \left( p_i \sum_{k \neq i} p_k \right) = \sum_{i=1}^J p_i (1 - p_i) = \sum_{i=1}^J (p_i - p_i^2) = \sum_{i=1}^J p_i - \sum_{i=1}^J p_i^2 = 1 - \sum_{i=1}^J p_i^2$$

- MART gain

$$\frac{1}{s} \left[ \sum_{i=1}^s (r_{i,k} - p_{i,k}) \right]^2 + \frac{1}{N-s} \left[ \sum_{i=s+1}^N (r_{i,k} - p_{i,k}) \right]^2 - \frac{1}{N} \left[ \sum_{i=1}^N (r_{i,k} - p_{i,k}) \right]^2$$

$r_{i,k} = 1$  if  $y_i = k$  and  $r_{i,k} = 0$  otherwise

$p_{i,k} = \mathbf{Pr}(y_i = k | \mathbf{x}_i)$

# Decision Trees

- Bagging
- Random Forest
- Gradient Boosting

# Gradient Boosting

$$p_{i,k} = \mathbf{Pr}(y_i = k | \mathbf{x}_i) = \frac{e^{F_{i,k}(\mathbf{x}_i)}}{\sum_{s=1}^K e^{F_{i,s}(\mathbf{x}_i)}}, \quad i = 1, 2, \dots, N,$$

where  $F_{i,k}(\mathbf{x}_i)$  is an additive model of  $M$  terms:  $F^{(M)}(\mathbf{x}) = \sum_{m=1}^M \rho_m h(\mathbf{x}; \mathbf{a}_m)$ ,

$$L = \sum_{i=1}^N L_i, \quad L_i = - \sum_{k=1}^K r_{i,k} \log p_{i,k}$$

where  $r_{i,k} = 1$  if  $y_i = k$  and  $r_{i,k} = 0$  otherwise.

$$\frac{\partial L_i}{\partial F_{i,k}} = -(r_{i,k} - p_{i,k}), \quad \frac{\partial^2 L_i}{\partial F_{i,k}^2} = p_{i,k} (1 - p_{i,k}).$$

# Gradient Boosting

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**Algorithm 1** Robust LogitBoost. MART is similar, with the only difference in Line 4.

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1:  $F_{i,k} = 0, p_{i,k} = \frac{1}{K}, k = 1$  to  $K, i = 1$  to  $N$

2: **for**  $m = 1$  to  $M$  **do**

3:   **for**  $k = 1$  to  $K$  **do**

4:      $\{R_{j,k,m}\}_{j=1}^J = J$ -terminal node regression tree from  $\{r_{i,k} - p_{i,k}, \mathbf{x}_i\}_{i=1}^N$ , with weights  $p_{i,k}(1 - p_{i,k})$ , using the tree split gain formula

5:     
$$\beta_{j,k,m} = \frac{K-1}{K} \frac{\sum_{\mathbf{x}_i \in R_{j,k,m}} r_{i,k} - p_{i,k}}{\sum_{\mathbf{x}_i \in R_{j,k,m}} (1-p_{i,k})p_{i,k}}$$

6:      $f_{i,k} = \sum_{j=1}^J \beta_{j,k,m} \mathbf{1}_{\mathbf{x}_i \in R_{j,k,m}}, \quad F_{i,k} = F_{i,k} + \nu f_{i,k}$

7:   **end for**

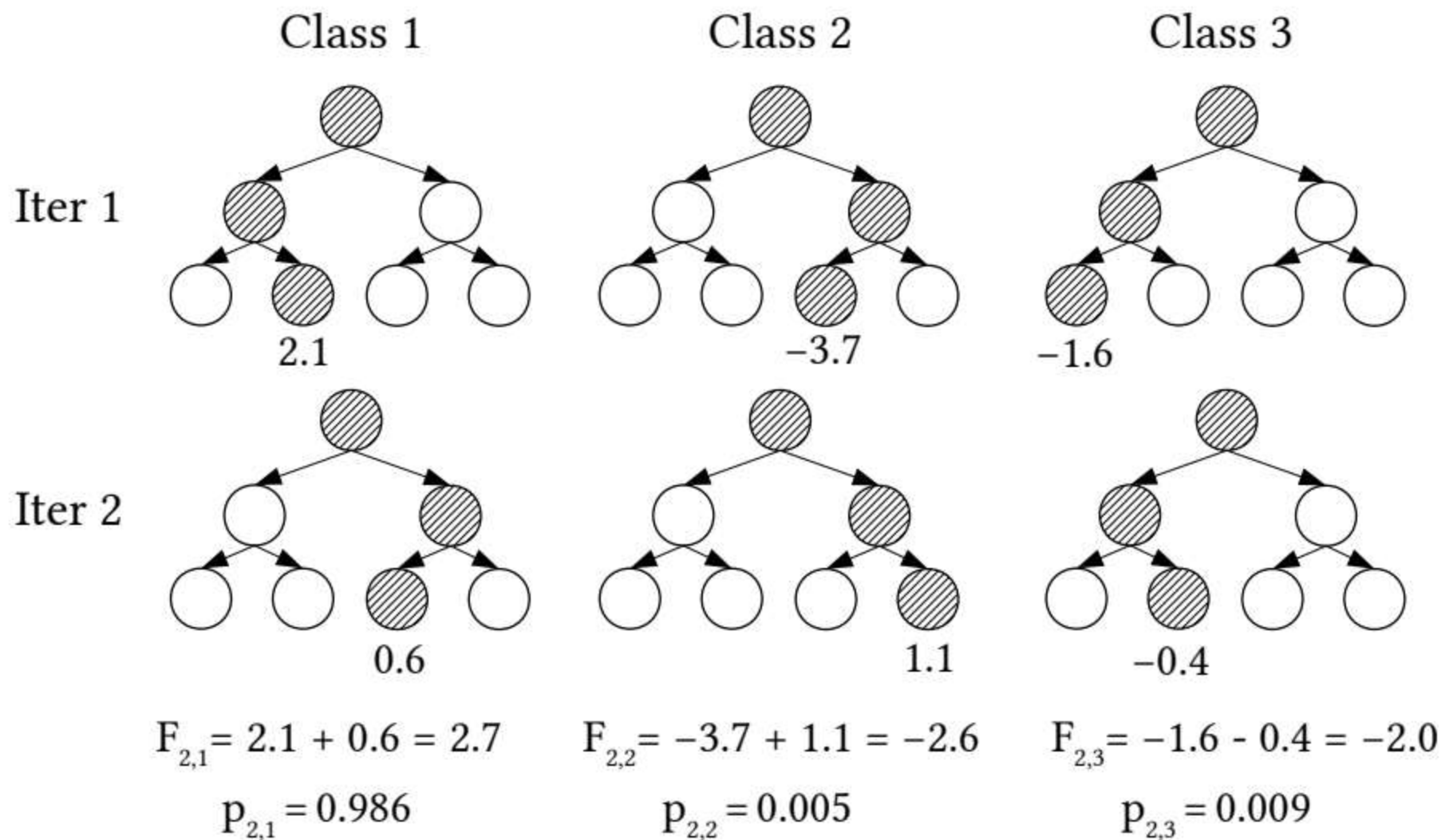
8:    $p_{i,k} = \exp(F_{i,k}) / \sum_{s=1}^K \exp(F_{i,s})$

9: **end for**

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# Gradient Boosting



# Data Reading

- Matrix Format
- CSV
- LIBSVM