Standard formula sheet

1. <u>Distributions</u>:

Normal
$$f(x|\mu,\sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

Binomial -
$$B(n,p)$$

$$P(X=k) = \binom{n}{k} p^k (1-p)^{n-k}$$

Poisson
$$P(X = k) = e^{-\lambda} \frac{\lambda^k}{k!}$$

Geometric
$$P(X = k) = (1 - p)^{k-1}p$$

2. <u>Decision Trees</u>:

Gini
$$Gini(S) = 1 - \sum_{i=1}^{c} \left(\frac{|S_i|}{|S|}\right)^2$$

Entropy
$$Entropy(S) = -\sum_{i=1}^{c} \frac{|S_i|}{|S|} \log \frac{|S_i|}{|S|}$$

3. Gradient descent and update steps

Linear regression
$$\theta_j \coloneqq \theta_j - \alpha \frac{1}{m} \sum_{d \in D} (h_{\theta}(x^{(d)}) - y^{(d)}) \cdot x_j^{(d)}$$

Perceptron
$$w_j \coloneqq w_j - \eta \sum_{d \in D} (o^{(d)} - t^{(d)}) x_j^{(d)}$$

Dual perceptron If
$$o^{(d)} \cdot t^{(d)} < 0$$
 then:

$$\alpha_j = \alpha_j + \eta$$

4. Logistic regression:

$$P(h(x) = 1) = \frac{1}{1 + e^{-w^T x}}$$

5. SVM

Primal objective function
$$\frac{1}{2}\|w\|^2 + \gamma \sum_d \xi_d - \sum_d \alpha_d (t_d(w^Tx_d + w_0) - 1 + \xi_d) - \sum_d \mu_d \xi_d$$

s.t
$$\alpha_d \ge 0$$
 $\mu_d \ge 0$

Dual objective function
$$\sum_d \alpha_d - 1/2 \sum_d \sum_e \alpha_d \alpha_e t_d t_e x_d^{\mathsf{T}} x_e$$

s.t
$$\sum_d \alpha_d t_d = 0$$
, $0 \le \alpha_d \le \gamma$

6. EM (for Bernoulli distributions):

New
$$w_{A_j} = \frac{1}{N} \sum_{i=1}^{N} r(x_i, A_j)$$

$$p_{A_j} = \frac{1}{(New \ W_{A_j})N} \sum_{i=1}^{N} r(x_i, A_j) v(i)$$

7. Linear Regression (closed form):
$$\theta^* = \underset{\theta}{\operatorname{argmin}} \|y - X \cdot \theta\|_2^2 = (X^T X)^{-1} X^T y$$