No Coding Farmer

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Abstract

Some Miscellaneous Summary.

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1 Expectation Maximization Introduction

1.1 EM Induction

$L(\theta) = \sum_{i=1}^{M} logp(X;\theta) = \sum_{i=1}^{m} log \sum_z p(X, Z;\theta)$
let θ_i be some distribution over z's ($\sum_z \theta_i(z) = 1, \theta_i(z) \geq 0$)
$\sum_i logp(X^{(i)};\theta)$
$= \sum_i log \sum_{Z^{(i)}} \theta_i(Z^{(i)}) \frac{p(X^{(i)},Z^{(i)};\theta)}{\theta_i(Z^{(i)})}$
$\geq \sum_i \sum_{Z^{(i)}} \theta_i(Z^i) log \frac{P(X^{(i))},Z^{(i)};\theta)}{\theta_i(Z^{(i))}} (f(x) = logx \quad is \quad concave.)$
let $\frac{P(X^{(i))},Z^{(i)};\theta)}{\theta_i(Z^{(i))}} = C$
the equality can be only reached when $\frac{P(X^{(i))},Z^{(i)};\theta)}{\theta_i(Z^{(i))}}$ is a constant.
we can get: $\sum_i \frac{p(X^{(i)},Z^{(i)};\theta)}{C} = 1$ namely: $\sum_i p(X^{(i)}, Z^{(i)};\theta) = C$
further induction: $\theta_i(Z^{(i)}) = \frac{p(X^{(i)},Z^{(i)};\theta)}{\sum_i p(X^{(i)},Z^{(i)};\theta)} = p(Z^{(i)}|X^{(i)};\theta)$
so the procedure of EM algorithm is:

Repeat Until Convergence:

- E-step: for each i,get $Q_i(Z^{(i)}) = p(Z^{(i)}|X^{(i)};\theta)$
- M-step: $\theta := argmax_\theta \sum_i \sum_{Z^i} i(Z^{(i)}) log \frac{p(X^{(i)},Z^{(i)}),\theta)}{Q_i(Z^{(i)})}$

1.2 EM convergence proof

let $l(\theta^{(t)}) = \sum_i \sum_{Z^{(i)}} Q_i^{(t)}(Z^{(i)}) log \frac{p(X^{(i)},Z^{(i)},\theta)}{Q_i^{(t)}(Z^{(i)})}$
then,we have the following inequality:
$l(\theta^{(t+1)})$
$\geq \sum_i \sum_{Z^{(i)}} Q_i^{(t)}(Z^{(i)}) log \frac{p(X^{(i)},Z^{(i)},\theta^{(t+1)})}{Q_i^{(t)}(Z^{(i)})}$
$\geq \sum_i \sum_{Z^{(i)}} Q_i^{(t)}(Z^{(i)}) log \frac{p(X^{(i)},Z^{(i)},\theta^{(t)})}{Q_i^{(t)}(Z^{(i)})}$
$\geq l(\theta^{(t)})$
the first inequality is because :$l(\theta) \geq \sum_i \sum_{Z^{(i)}} Q_i^{(t)}(Z^{(i)}) log \frac{p(X^{(i)},Z^{(i)},\theta)}{Q_i^{(t)}(Z^{(i)})} \forall \theta, Q_i$
the second inequality is because of the maximum of the M-step.

Hence, EM causes the likelihood to converge monotonically.

1.3 Different Writing Style of EM Algorithm

There are many writing style of EM algorithm. here I just mention the book <Statistics Learning Method> by LiHang who is very famous in China.

EM algorithm from LiHang(Li-version):

Algorithm 1 EM from LIHang

Require: observation X,hidden variable Z,joint distribution $P(X, Z|\theta)$,conditional distribution $P(Z|Y, \theta)$

while Not convergence **do**

E-Step: let $\theta^{(i)}$ is the i-th estimate of θ,

$Q(\theta, \theta^{(i)}) = E_z[logP(X, Z|\theta)|X, \theta^{(i)}] = \sum_Z logP(X, Z|\theta)P(Z|X, \theta^{(i)})$

M-step: $\theta^{(i+1)} = argmax_\theta Q(\theta, \theta^{(i)})$

end while

output model parameter θ

it seems that Li-version is different from the above version. however, they are the same. because:

- the above version just consider every data, so that it include subscript i. however Li-version only consider one data.
- the above version can be transformed to Li-version.

  $\sum_Z Q(Z)log\frac{P(X,Z:\theta)}{Q(Z)}$
  $= \sum_Z P(Z|X;\theta^{(t)})log\frac{p(X,Z;\theta)}{p(Z|X;\theta^{(t)})}$
  $= \sum_Z P(Z|X;\theta^t)logP(X,Z;\theta) - \sum_Z P(Z|X;\theta^{(t)})logP(Z|X;\theta^{(t)})$

  as the variable is θ,so $\sum_Z P(Z|X;\theta^{(t)})logP(Z|X;\theta^{(t)}$ can be removed.
- $Q(\theta, \theta^{(i)}) = \sum_Z logP(X, Z|\theta)P(Z|X, \theta^{(i)})$ can be also written as $Q(\theta, \theta^{(i)}) = \sum_Z logP(X, Z|\theta)P(Z, X, \theta^{(i)})$,because X is a observation.

2 EM applications

2.1 Gaussian Mix Model

GMM can be solved by EM. **notice here we use the expectation of EM:**

$Q(\theta, \theta^{(i)})$
$= E_\gamma[logP(y, \gamma|\theta)|y, \theta^{(i)}]$
$= E[\sum_{k=1}^K[n_k log\alpha_k + \sum_{j=1}^N \gamma_{jk}[log\frac{1}{\sqrt{2\pi}} - log\sigma_k - \frac{1}{2\sigma_k^2}(y_j - \mu_k)^2]]]$
$= \sum_{k=1}^K[(E\gamma_{jk})log\alpha_k + \sum_{j=1}^N(E\gamma_{jk})[log\frac{1}{\sqrt{2\pi}} - log\sigma_k - \frac{1}{2\sigma_k^2}(y_j - \mu_k)^2]]$

here $(E\gamma_{jk})$ can be easily calculated.

$\hat{\mu_k}, \hat{\sigma_k^2}$ can be acquired by derivation.

$\hat{\alpha_k}$ can be acquired by the derivation on the Lagrangian($\sum_i^K \alpha_k = 1$).

2.2 Hidden Markov Model

HMM Learning Method is also called Baum-Welch algorithm.the target is learning $\lambda = (A, B, \pi)$.

Q function is:

$Q(\lambda, \bar{\lambda}) = \sum_I logP(O, I|\lambda)P(O, I|\bar{\lambda})$

$P(O, I, \lambda) = \pi_{i1}b_{i1}(o_1)a_{i1i2}b_{i2}(o_2)...a_{i_{T-1}i_T}b_{i_T}(o_T)$

so the Q function can also be written as:

$$Q(\lambda, \bar{\lambda}) =$$
$$\sum_I log\pi_{i1} P(O, I|\bar{\lambda}) + \sum_I (\sum_{t=1}^{T-1} loga_{i,i+1}) P(O, I|\bar{\lambda}) + \sum_I (\sum_{t=1}^{T} logb_{it}(o_t)) P(O, I|\bar{\lambda})$$

note here: I is not only one state. it includes state length from 1 to T,which all start from i_1

so we can solve the maximum of Q function by derivation on the Lagrangian polynomial (because exists these limitations: $\sum_{i=1}^{N} \pi_i = 1, \sum_{j=1}^{N} a_{ij} = 1, \sum_{i=1}^{M} b_i = 1$)

2.3 Naive Bayesian

2.4 other papers

We can use softmax to model transition probability, normal distribution to model emission probability.

it's a good example in Car that Knows Before You Do: Anticipating Maneuvers via Learning Temporal Driving Models, the AIO-HMM can be more complicated,which can be enriched by the graphic model by M.I Jordon.

3 VAE

here is a complete VAE tutorial [1]

$$max \quad logP(x)$$
$$\text{lhs} = log \int P(x, z) dz$$
$$= log \int P(x/z) p(z) dz$$
$$= \log \int \frac{P(x/z)}{q(z/x)} q(z/x) p(z) dz$$
$$= logE_{q(z/x)}[\frac{p(x/z)}{q(z/x)} p(z)]$$
$$\text{jenson's inequality,we can know: } \geq E_{q(z/x)}[log\frac{p(x/z)}{q(z/x)} p(z)]$$
$$= E_{q(z/x)}[logp(x/z)] + E_{q(z/x)}[log\frac{p(z)}{q(z/x)}]$$
$$= E_{q(z/x)}[logp(x/z)] - E_{q(z/x)}[log\frac{q(z/x)}{p(z)}]$$
$$= E_{q(z/x)}[logp(x/z)] - KL(q(z/x)||p(z))$$

4 ADMM

minimize H(u) + G(v)
subject to Au + Bv = b

$max_\lambda min_{u,v} H(u) + G(v) + < \lambda, b - Au - Bv > + \frac{\tau}{2} ||b - Au - Bv||^2$

Alternating Direction Method of Multipliers
$u_{k+1} = argmin_u H(u) + < \lambda_k, -Au > + \frac{\tau}{2} ||b - Au - Bv_k||^2$
$v_{k+1} = argmin_v G(v) + < \lambda_k, -Bv > + \frac{\tau}{2} ||b - Au_{k+1} - Bv||^2$
$\lambda_{k+1} = \lambda_k + \tau(b - Au_{k+1} - Bv_{k+1})$

Distributed Problems
minimize g(x) + $\sum_i f_i(x)$
example: sparse least squares:
minimize $\mu||x||_1 + \frac{1}{2}||Ax - b||^2$

minimize $\mu||x||_1 + \sum_i \frac{1}{2}||A_i x - b_i||^2$

data stored on different servers

Transpose Reduction
minimize $\frac{1}{2}||Ax-b||^2$
$x^* = (A^TA)^{-1}A^Tb$

distributed compution:
$A^Tb = \sum A_i^T b_i$
$A^TA = \sum A_i^T A_i$

Unwrapped ADMM
minimize $g(x) + f(Ax) = g(x) + \sum_i f_i(A_i x)$

Example: SVM
minimize $\frac{1}{2}||x||^2 + h(Ax)$
A = data,h = hinge loss

Unwrapped form
minimize $\frac{1}{2}||x||^2 + h(z)$
subject to z=Ax

Transpose Reduction ADMM
scaled augmented Lagrangian:
minimize $\frac{1}{2}||x||^2 + h(z) + \frac{\tau}{2}||z - Ax - \lambda||^2$

ADMM:
$x^{k+1} = min_x \frac{1}{2}||x||^2 + \frac{\tau}{2}||z^k - Ax + \lambda^k||^2$
$z^{k+1} = min_z h(z) + \frac{\tau}{2}||z - Ax^{k+1} + \lambda^k||^2$
$\lambda^{k+1} = \lambda^k + z^{k+1} - Ax^{k+1}$

Minimization Steps
minimize $l(a_3) + \frac{1}{2}||z_2 - W_1 a_1||^2 + \frac{1}{2}||a_2 - \sigma(z_2)||^2 + \frac{1}{2}||z_3 - W_2 a_2||^2 + \frac{1}{2}||a_3 - \sigma(z_3)||^2$

Solve for weight: least squares(convex)
Solve for activations: least squares + ridge penalty(convex)
Solve for inputs: coordinate-minimization (non-convex but global)

Lagrange Multipliers
minimize $l(a_3) + \frac{1}{2}||z_2 - W_1 a_1||^2 + \frac{1}{2}||a_2 - \sigma(z_2)||^2 + < \lambda_1, z_2 - W_1 a_1 > + < \lambda_2, a_2 - \sigma(z_2) > + \frac{1}{2}||z_3 - W_2 a_2||^2 + \frac{1}{2}||a_3 - \sigma(z_3)||^2 + < \lambda_3, z_3 - W_2 a_2 > + < \lambda_4, a_3 - \sigma(z_3) >$

unstable because of non-linear constraints

Bregman Iteration
minimize $l(a_3) + < \lambda, a_3 > + \frac{1}{2}||z_2 - W_1 a_1||^2 + \frac{1}{2}||a_2 - \sigma(z_2)||^2 + \frac{1}{2}|||z_3 - W_2 a_2||^2 + \frac{1}{2}||a_3 - \sigma(z_3)||^2$

HOG feature dimension: 648

mid layer 1 num: 100

mid layer 2 num: 50

output layer: 1

Algorithm 2 ADMM_NN

Inputs:

data number:n=10000,
data dimension: m=648,
hidden layer 1 unit number: a=100
hidden layer 2 unit number: b=50
output layer unit number: 1
a_0 m-n dimension,
W_1 : a-m dimension
z_1 : a-n dimension
a_1 : a-n dimension
W_2 : b-a dimension
z_2 : b-n dimension
a_2 : b-n dimension
W_3 : 1-b dimension
z_3 : 1-n dimension
labels:y 1-n dimension
λ : 1-n dimension
activation function h is ReLu.

Initialize:

allocate $\{a_l\}_{l=1}^{L}$,$\{z_l\}_{l=1}^{L}$ with i.i.d Gaussian Distribution,and λ

Cache: $a_0^\dagger$
Warm Start:
for i=1,..,100 **do**
for l=1,2,...,L-1 **do**
$W_l \leftarrow z_l a_{l-1}^\dagger$
$a_l \leftarrow (\beta_{l+1} W_{l+1}^T W_{l+1} + \gamma_l I)^{-1}(\beta_{l+1} W_{l+1}^T z_{l+1} + \gamma_l h_l(z_l))$
$z_l \leftarrow argmin_z \gamma_l ||a_l - h_l(z)||^2 + \beta_l ||z - W_l a_{l-1}||^2$

end for
$W_L \leftarrow z_L a_{L-1}^\dagger$
$z_L \leftarrow argmin_z l(z,y) + < z, \lambda > + \beta_L ||z - W_L a_{L-1}||^2$
end for
Start ADMM:
while not converge **do**
for l=1,2,...,L-1
do $W_l \leftarrow z_l a_{l-1}^\dagger$
$a_l \leftarrow (\beta_{l+1} W_{l+1}^T W_{l+1} + \gamma_l I)^{-1}(\beta_{l+1} W_{l+1}^T z_{l+1} + \gamma_l h_l(z_l))$
$z_l \leftarrow argmin_z \gamma_l ||a_l - h_l(z)||^2 + \beta_l ||z - W_l a_{l-1}||^2$
end for
$W_L \leftarrow z_L a_{L-1}^\dagger$
$z_L \leftarrow argmin_z l(z,y) + < z, \lambda > + \beta_L ||z - W_L a_{L-1}||^2$
$\lambda \leftarrow \lambda + \beta_L (z_L - W_L a_{L-1})$
end while

z_l argmin procedure:

$$z_l = \begin{cases} max(\frac{a_l \gamma_l + W_l a_{l-1} \beta_l}{\gamma_l + \beta_l}, 0) & \text{z} \geq 0 \\ min(W_l a_{l-1}, 0) & \text{z} \leq 0 \end{cases}$$

choose one minimizer z from two choices.

z_L argmin procedure:

when $y_i = 0$:
$f(z) = \beta z^2 - (2\beta w\_a - \lambda)z + max(z, 0)$

$z^* = max(\frac{2\beta w\_a-\lambda-1}{2\beta}, 0)$ or
$z^* = min(\frac{2\beta w\_a-\lambda}{2\beta}, 0)$
choose one which make f(z) smaller.

when $y_i = 1$:
$f(z) = \beta z^2 - (2\beta w\_a - \lambda)z + max(1 - z, 0)$
$z^* = max(\frac{2\beta w\_a-\lambda}{2\beta}, 1)$ or
$z^* = min(\frac{2\beta w\_a-\lambda+1}{2\beta}, 1)$
choose one which make f(z) smaller.

z_L argmin procedure(when l is a standard hinge loss):

when $y_i = -1$: $f(z) = max(1 + z) + \lambda z + \beta(z^2 - 2w\_az)$
$z^* = min(\frac{2\beta w\_a-\lambda}{2\beta}, -1)$ or
$z^* = max(\frac{2\beta w\_a-\lambda-1}{2\beta}, -1)$ choose one which make f(z) smaller.

when $y_i = 1$:
$f(z) = max(1 - z, 0) + \lambda z + \beta(z^2 - 2w\_az)$
$z^* = min(\frac{2\beta w\_a-\lambda+1}{2\beta}, 1)$ or
$z^* = max(\frac{2\beta w\_a-a-\lambda}{2\beta}, 1)$
choose one which make f(z) smaller.

5 Key steps you must know when building a DL Framework

5.1 Convolution

6 R-PCA

RPCA problem:
$min_{A,E}\ ||A||_* + \lambda||E||_1$
S.t D=A+E

RPCA dual problem:

Augmented Lagrangian is :
$A_t(A, E; \Lambda) = min\_A, EL(A, E; \Lambda)$
$= min_{A,E}||A||_* + \Lambda||E||_1 + < \Lambda, D - A - E >$
$= min_A||A||_* - < \Lambda, A > + min_E\lambda||E||_1 - < \Lambda, E > + < \Lambda, D >$

both of the sub-problem is conjugate function,according to the property of conjugate function :

$A_t(A, E; \Lambda) = < \Lambda, D >$
$S.t \quad ||\Lambda||_2 \leq 1, ||\Lambda||_\infty \leq \lambda$

so the dual problem is:
$max_\Lambda \quad < \Lambda, D >$
$S.t \quad ||\Lambda||_2 \leq 1, ||\Lambda||_\infty \leq \lambda$

6.1 Solve RPCA by ADMM

the ADMM sub-problem is:
A-sub-problem:
$A_{k+1} = argmin_A||A||_* + \frac{\beta}{2}||D - A - E_k + \Lambda_k/\beta||_F^2$

E-sub-problem:
$E_{k+1} = argmin_E\lambda||E||_1 + \frac{\beta}{2}||D - A_{k+1} - E + \Lambda_k||_F^2$

E-sub-problem has closed-form solution as follows:
$E_{k+1} = S_{\lambda\beta^{-1}}(D - A_k + \Lambda_k/\beta)$.

$S_\epsilon = sgn(x)max(|x| - \epsilon, 0)$,which is the same form as shrinkage.

A-sub-problem has a closed-form solution offered by Singular Value Thresholding(SVT):suppose that the SVD of $W = D - E_k + \Lambda_k/\beta_k$ is $W = U\Sigma V^T$,then the optimal solution is $A = US_{\beta^{-1}}(\Sigma)V^T$.

6.2 Adaptive Penalty for ADMM

Lin et al.[2] suggest updating the penalty parameter β as follows:
$\beta_{k+1} = min(\beta_{max}, \rho\beta_k)$
where ρ_{max} is an upper bound of $\{\beta_k\}$. the value of ρ is defined as:

$$\rho = \begin{cases} \rho_0 & if \frac{\beta_k max(\sqrt{\eta_A}||x_{k+1}-x_k||_2, \sqrt{\eta_B}||y_{k+1}-y_k||_2)}{||c||_2} < \epsilon_2 \\ 1 & otherwise \end{cases}$$

where η_A, η_B is linearized Taylor second-order factor.

7 SFM

`https://www.robots.ox.ac.uk/~vgg/hzbook/hzbook2/HZepipolar.pdf`

- $\mathtt{F}$ is a rank 2 homogeneous matrix with 7 degrees of freedom.
- **Point correspondence**: If $\mathbf{x}$ and $\mathbf{x}'$ are corresponding image points, then $\mathbf{x}'^{\mathsf{T}}\mathtt{F}\mathbf{x} = 0$.
- **Epipolar lines**:
  - $\mathbf{l}' = \mathtt{F}\mathbf{x}$ is the epipolar line corresponding to $\mathbf{x}$.
  - $\mathbf{l} = \mathtt{F}^{\mathsf{T}}\mathbf{x}'$ is the epipolar line corresponding to $\mathbf{x}'$.
- **Epipoles**:
  - $\mathtt{F}\mathbf{e} = \mathbf{0}$.
  - $\mathtt{F}^{\mathsf{T}}\mathbf{e}' = \mathbf{0}$.
- **Computation from camera matrices** $\mathtt{P}, \mathtt{P}'$:
  - General cameras,
    $\mathtt{F} = [\mathbf{e}']_\times \mathtt{P}'\mathtt{P}^+$, where $\mathtt{P}^+$ is the pseudo-inverse of $\mathtt{P}$, and $\mathbf{e}' = \mathtt{P}'\mathbf{C}$, with $\mathtt{P}\mathbf{C} = \mathbf{0}$.
  - Canonical cameras, $\mathtt{P} = [\mathtt{I} \mid \mathbf{0}]$, $\mathtt{P}' = [\mathtt{M} \mid \mathbf{m}]$,
    $\mathtt{F} = [\mathbf{e}']_\times \mathtt{M} = \mathtt{M}^{-\mathsf{T}}[\mathbf{e}]_\times$, where $\mathbf{e}' = \mathbf{m}$ and $\mathbf{e} = \mathtt{M}^{-1}\mathbf{m}$.
  - Cameras not at infinity $\mathtt{P} = \mathtt{K}[\mathtt{I} \mid \mathbf{0}]$, $\mathtt{P}' = \mathtt{K}'[\mathtt{R} \mid \mathbf{t}]$,
    $\mathtt{F} = \mathtt{K}'^{-\mathsf{T}}[\mathbf{t}]_\times \mathtt{R}\mathtt{K}^{-1} = [\mathtt{K}'\mathbf{t}]_\times \mathtt{K}'\mathtt{R}\mathtt{K}^{-1} = \mathtt{K}'^{-\mathsf{T}}\mathtt{R}\mathtt{K}^{\mathsf{T}}[\mathtt{K}\mathtt{R}^{\mathsf{T}}\mathbf{t}]_\times$.

Figure 1: Summary of Fundamental matrix properties

8 Reinforcement Learning

Markov Decision Process (**MDP**) is tuple$(\mathcal{S}, \mathcal{A}, \mathcal{P}, r, \gamma)$:

r is a reward function,$r(s, a, s^{'})$

γ is a discount factor

$\mathcal{P}$ is the transition probability distribution:
probability from state s with action a to state $s^{'}$: $P(s^{'}|s, a)$

$\mathcal{S}$ is a finite set of states.

$\mathcal{A}$ is a finite set of actions.

Markov Property:
$P(s_{t+1}|s_t) = P(s_{t+1}|s_1, ..., s_t)$

Stochastic Policy:
$\pi(a|s) = P(a_s = a|s_t = s)$

Value function:
$G_t = r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + ... = \sum_{k=0}^{\infty} \gamma^k r_{t+k+1}$

State-value function:
$V_\pi(s) = E_\pi(G_t|s_t = s)$

Action-value function:
$Q_\pi(s, a) = E_\pi(G_t|s_t = s, a_t = a)$

Bellman Equation:
$V_\pi(s) = E_\pi(r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + ...|s_t = s)$
$= E_\pi(r_{t+1} + \gamma(r_{t+2} + \gamma r_{t+3} + ...)|s_t = s)$
$= E_\pi(r_{t+1} + \gamma G_{t+1}|s_t = s)$
$= E_\pi(r_{t+1} + \gamma V_\pi(s_{t+1})|s_t = s)$

For state-value function, Bellman Equation can be written as:
$V_\pi(s) = E_\pi(r_{t+1} + \gamma V_\pi(s_{t+1})|s_t = s)$
$= \sum_{\alpha \in A} \pi(a|s) \sum_{s' \in S} P(s^{'}|s, a)[r(s, a, s^{'}) + \gamma V_\pi(s^{'})]$
$r(s, a, s^{'})$ is same with r_{t+1} to some extent.

For action-value function, Bellman Equation can be written as:
$Q_\pi(s, a) = E_\pi(r(s, a, s^{'}) + \gamma Q_\pi(s^{'}, a^{'})|s, a)$
$= \sum_{s' \in S} P(s^{'}|s, a)[r(s, a, s^{'}) + \gamma \sum_{a' \in A} \pi(a^{'}, s^{'}) Q_\pi(s^{'}, a^{'}))]$

Normally, we just assume the $\pi(a|s), p(s^{'}|s, a), r(s, a, s^{'})$ are known(namely the MDP is known). so we can solve the linear equation above. however, when data become huge, it is not feasible to solve the Bellman Equation directly.

optimal value function:

the optimal state-value function $V_*(s)$ is :
$V_*(s) = max_\pi V_\pi(s)$

the optimal action-value function $q_*(s, a)$ is:
$q_*(s, a) = max_\pi Q_\pi(s, a)$

The goal for any MDP is finding the optimal value function.

Or equivalent an optimal policy π^* for any policy $\pi, V_{\pi^*}(s) \geq V_\pi(s), \forall s \in S$

Acknowledgments

References

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[2] Zhouchen Lin, Risheng Liu, and Zhixun Su. Linearized alternating direction method with adaptive penalty for low-rank representation. In J. Shawe-Taylor, R. S. Zemel, P. L. Bartlett, F. Pereira, and K. Q. Weinberger, editors, *Advances in Neural Information Processing Systems 24*, pages 612–620. Curran Associates, Inc., 2011.