Optimization, Methodology and Application Challenges in Deep Learning

Deep Learning Decal

Hosted by Machine Learning at Berkeley

Agenda

Background

The Optimization Perspective

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$$\min_{\theta} \mathbb{E}_{\theta} J(h(x, \theta), y)$$

- Instead minimize empirical risk given by test set:

$$\min_{\theta} \frac{1}{n} \sum_{i=1}^{n} J(h(x^{(i)}, \theta), y^{(i)})$$

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- Typical batch sizes: powers of 2 between 32 and 256. Small batch $\rightarrow$ regularizing effect since more noise. Best generalization comes from batch size being 1.

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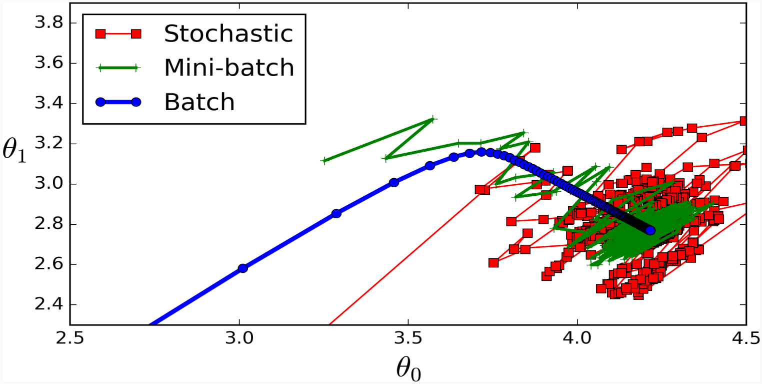

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- If $\mathbf{H}$ becomes ill-conditioned, learning slows because ϵ shrinks accordingly.

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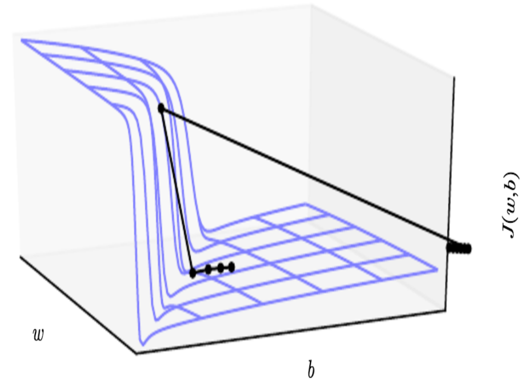
- **cliffs and exploding gradients**: extremely steep gradients that may "catapult" values so far it undoes previous learning.
- **vanishing gradients**: gradient calculated w.r.t. parameters "far away" (either temporally in RNN's or spatially in deep networks) vanishes.

Challenges Continued



Main Algorithms

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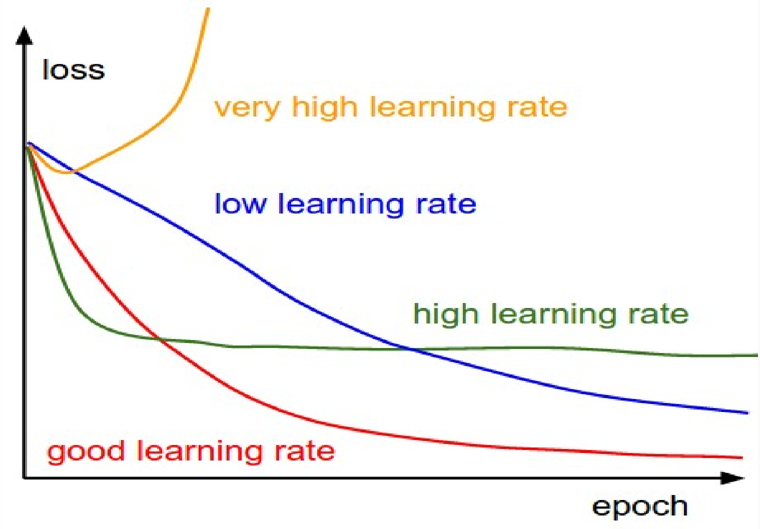
Commonly we have ϵ decay linearly until iteration τ like so, with $\alpha = \frac{k}{\tau}$

$$\epsilon_k = (1-\alpha)\epsilon_0 + \alpha\epsilon_\tau$$

Best Learning Rate Practices



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  Same as $\mathbf{v} \leftarrow \alpha\mathbf{v} - \epsilon\mathbf{g}$
- Update parameters: $\theta \leftarrow \theta + \mathbf{v}$ Common values of α include 0.5, 0.9 and 0.99. Good to adapt α by increasing it (ϵ still more important).

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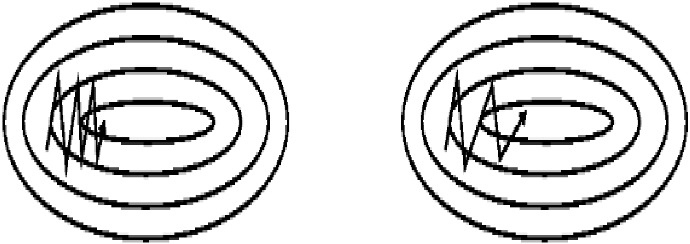

(a) SGD without momentum

(b) SGD with momentum

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Still, having only one ϵ for all parameters is not nuanced.

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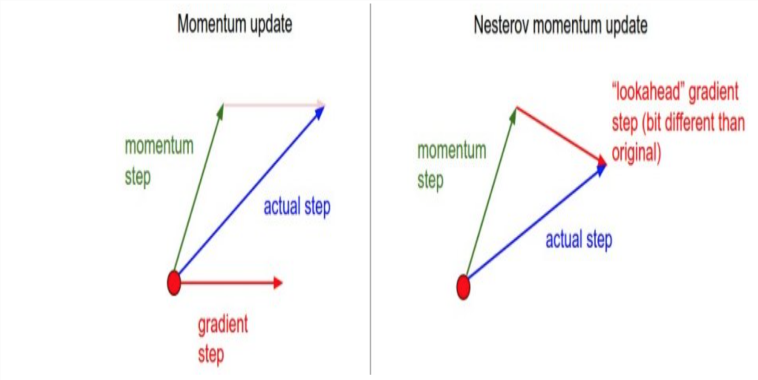

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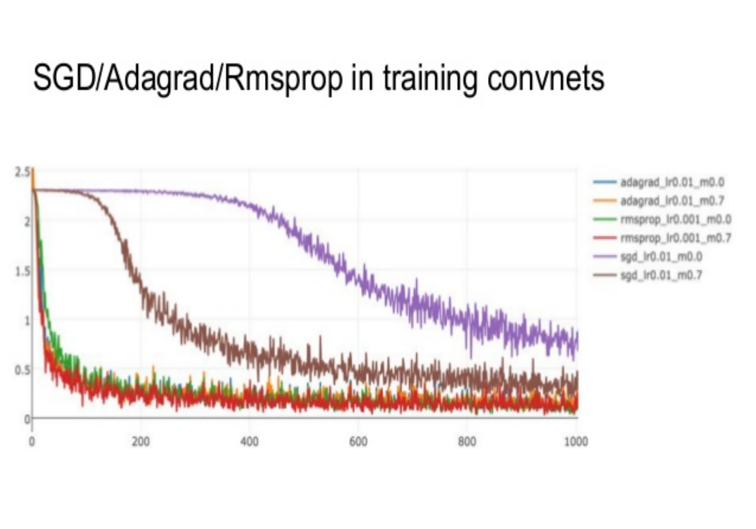
- **AdaGrad** *(Adaptive Gradient Algorithm)*: Gradient is inversely proportional to square root of average sum of all historical squared values.
    - Issue: First values of gradient are often bad and end up skewing the average.
- **RMSProp** *(Root-Mean-Square Propagation)*: Gradient is inversely proportional to an exponentially weighted moving average $\rightarrow$ resolves issue with AdaGrad.


SGD/Adagrad/Rmsprop in training convnets
2.5
2
1.5
1
0.5
0
0
200
400
600
800
1000
adagrad_lr0.01_m0.0
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All of these are available to use as optimization algorithms in modern libraries e.g. Tensorflow.

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Normalized initialization compromise: layers having same activation variance and having same gradient variance

Newton's Method

Newton's Method utilizes second-derivative information via Taylor Expansion of $J(\theta)$ at some point θ_0:

$$J(\theta) \approx J(\theta_0) + (\theta - \theta_0)^T \nabla_\theta J(\theta_0) + \frac{1}{2}(\theta - \theta_0)^T \mathbf{H}(\theta - \theta_0)$$

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- If convex ($\mathbf{H}$ is always positive definite), then this finds solution after finite iterations.
- If nonconvex, regularize $\mathbf{H}$ to be positive definite for approximate solution: $\mathbf{H} \leftarrow \mathbf{H} + \alpha \mathbf{I}$

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- (L-)BFGS Algorithm: Approximates Hessian, takes $\mathcal{O}(k^2)$ memory, can be made $\mathcal{O}(k)$ with limited memory version.

Other Second Order Methods

Conjugate gradient

MIT 10.637 Lecture 3

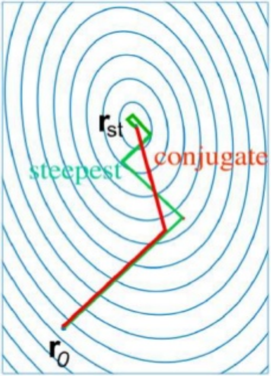
Improvement over SD method.
First step is same as SD:

$$\mathbf{q}_2 = \mathbf{q}_1 - \lambda_1 \nabla E_1$$

determined via line search.

Subsequent steps: linear combination of negative gradient and preceding search direction.

Pro: Using history, faster convergence near minimum.



Meta-Algorithms and Heuristics

Regularization - Weight Decay

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- Hence, a theoretically valid implementation of neural network regularization is that after each parameter update, multiply all weights by a number just below 1.

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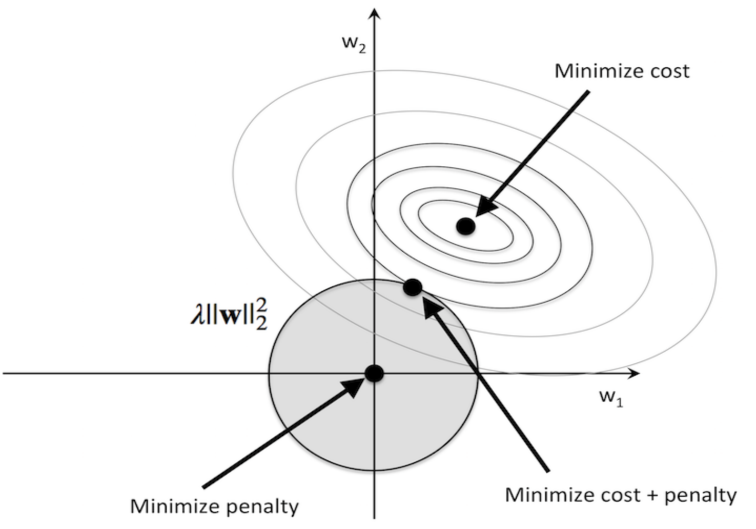

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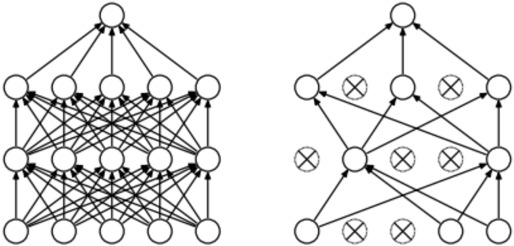
- Each unit is kept on for training with probability p. Thus, backpropagation affects only those units' weights.



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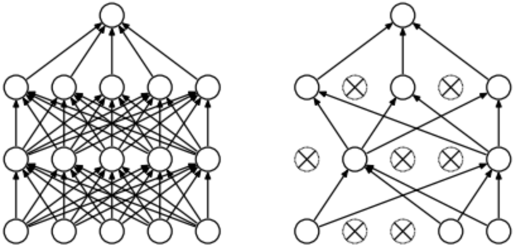
- Efficient form of model-averaging.



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- Backpropagation works through this function so earlier layers are still treated correctly.

Batch Normalization (Contd.)

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- During training, compute μ, σ for each batch. During test, use averaged values.
- To maintain expressiveness, replace $\mathbf{M}$ with $\gamma \mathbf{M}' + \beta$. Mean and Stdv. come from single learned parameters rather than complex layer interactions.

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Can conclude process with a **fine-tuning** stage where the entire network is trained together.

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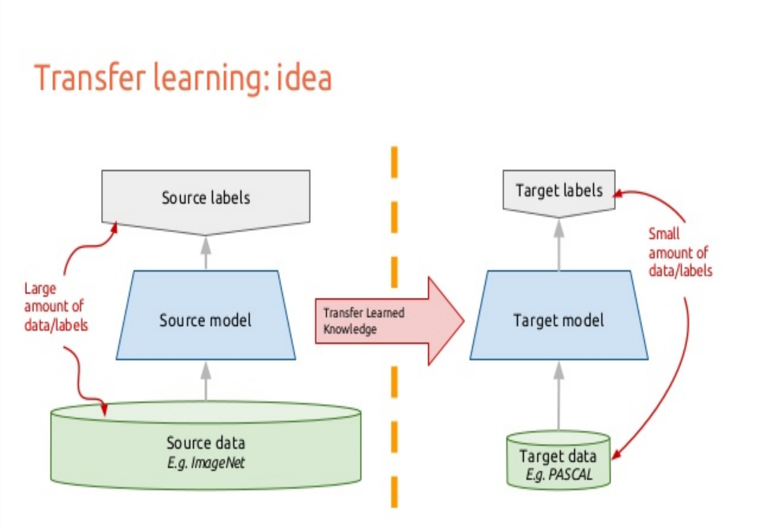
    - Student minimizes traditional loss, predicts the hidden layer state of Teacher. Student gets hints and improves overall generalization.

Supervised Pre-Training (Contd.)



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Issues include computational cost to compute $J^{(i)}$ since it depends on sampling and if the function cannot be effectively be blurred.

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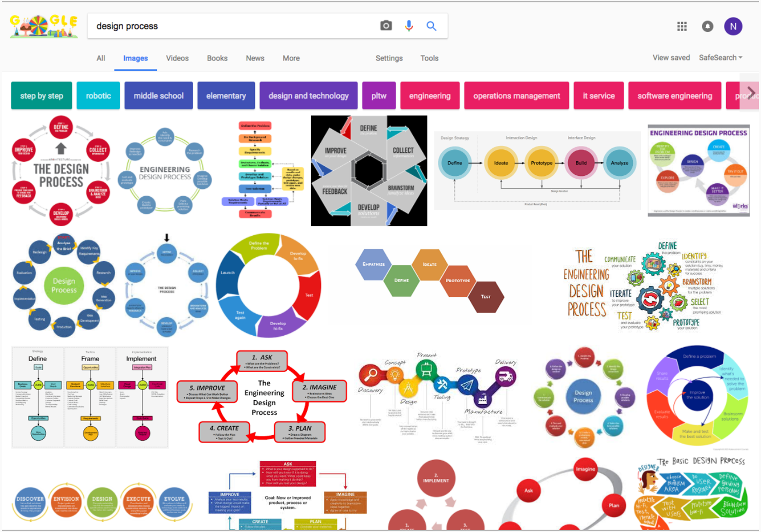
- Verified as **consistent with how humans teach**.

Methodology

Design Process Overview



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- **Iterate over incremental changes:** Gather more data, tune hyperparameters, change algorithms.

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We can plot precision and recall on a **PR curve**. Trade precision for recall by changing the detection threshold.

Performance Metrics (Contd.)

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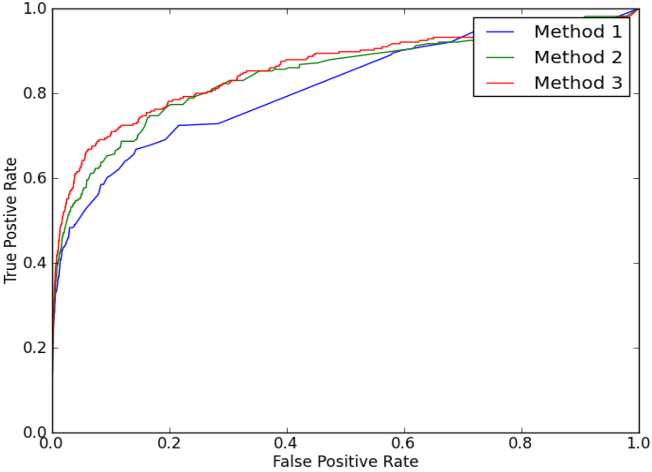
- Scalar score for precision, recall is **F-score:** $\frac{2pr}{p+r}$.

We can also let the model refuse to give output if not confident. Fraction of examples for which model can give response is called **coverage.** Can trade accuracy for coverage.

Performance Metrics (Contd.)



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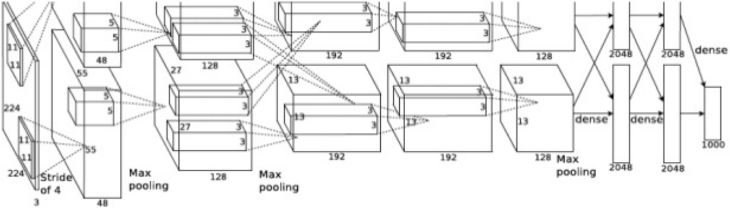
- Determine if unsupervised learning can help by making representations.
- Try plotting performance for different amounts of data to extrapolate how much is needed to reach a performance level.

AlexNet

- Similar framework to LeCun'98 but:
  - Bigger model (7 hidden layers, 650,000 units, 60,000,000 params)
  - More data (10^6 vs. 10^3 images)
  - GPU implementation (50x speedup over CPU)
    - Trained on two GPUs for a week



A. Krizhevsky, I. Sutskever, and G. Hinton,
ImageNet Classification with Deep Convolutional Neural Networks, NIPS 2012

Manual Hyperparameter Tuning

Primary goal: Match **effective capacity** of model to **complexity** of task.

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- Consider how # of hidden layer units, dropout probability, convolution kernel width, etc. **capacity**. Bias-Variance Tradeoff.

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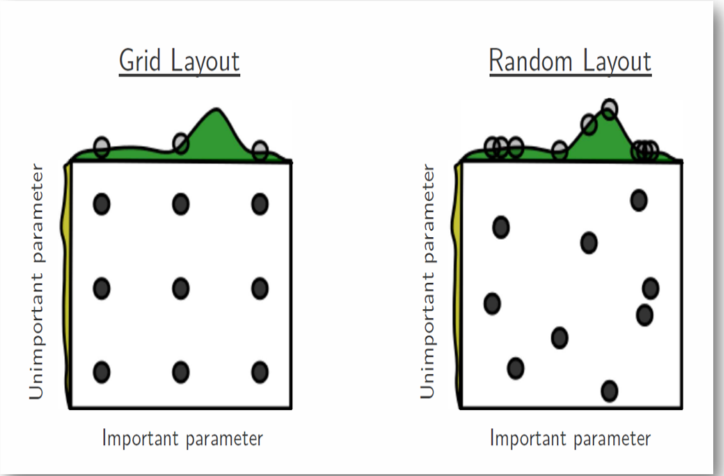
- **Bayesian Optimization**: Treat hyperparams as decision variables in meta-optimization problem. Try to maximize performance iteratively.

Automatic Hyperparameter Tuning



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Application Strategies

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- **Asynchronous SGD** - noisier parameter updates, but faster overall progress

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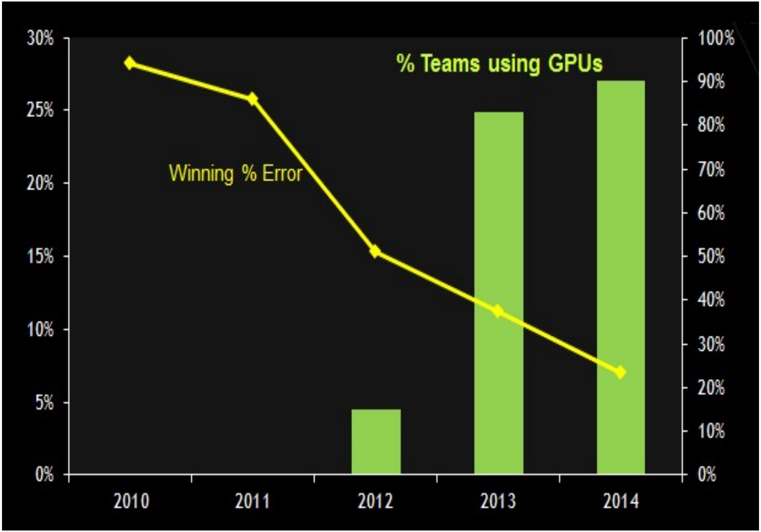

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- Train simpler model g on $(X, f(X))$ to try and approximate f with fewer parameters.

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- Hard MOE (pick only one expert) will save lots of time compared to regular MOE.

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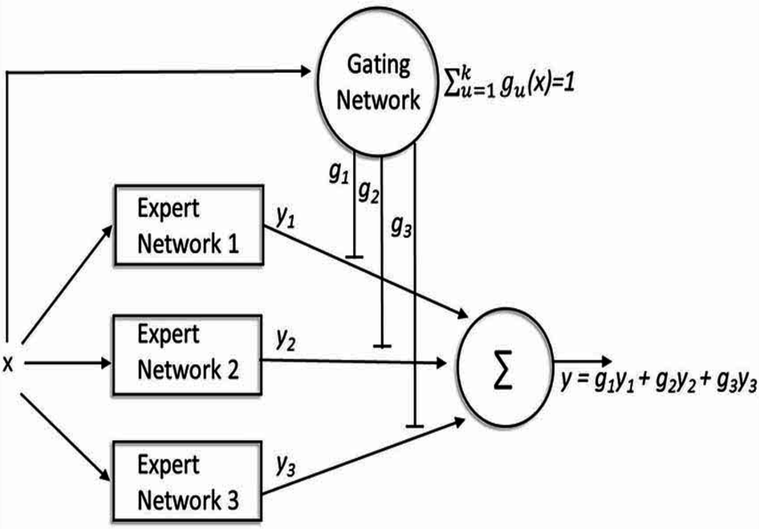

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- Having to do realtime analysis like for self-driving cars, conversational AI
- If we want deep learning to be in IoT, important to develop efficient, fast, small implementations.

Conclusion

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- Can make huge impact by compressing, simplifying existing models.

Questions

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