ECE763 Computer Vision: Models, Learning and Inference (including Deep Learning)

Project 03

Due (see moodle) No late days

(Grades: 100 points in total)

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Grading Policy

- **Homework**: 7% x 5 = 35%
- **Projects**: 60% + [5% bonus]
  - Project 1 (10%) & 2 (20%): **work individually [not required if you work on thrust 1 and 2 in the next slide)**
  - Project 3 (course project): 30%, **a group (<= 3 members) is allowed [not required for all thrusts in the next slide)**
    - You can propose your own projects and work on it once agreed by both of you and me.
    - Requirement: final write-up (15%) and self-contained reproducible code (15%)
    - Bonus points (5%): for top-3 winner of the final project
- **Attendance**: 5% (via in-class moodle quiz, 10min before and 15min after class, from the 2nd week)
- **Late policy**
  - 5 free late days – use them in your ways (counted using 0.5 unit, <=6 hours as 0.5 late day, otherwise 1 later day)
  - Afterwards, 25% off per day late
  - Not accepted after 3 late days per HW and Project 1 & 2
  - Does not apply to Project 3 (no late assignments allowed).
  - We will **NOT** accept any replacement of submission after deadline, even if you can show the time stamp of the replacement is earlier than the deadline. So, please double-check if you submit correct files.
- **Other policies**: please see details in the syllabus.

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Discussions on Projects

- Thrust I: If applicable, identify problem(s) in your own field that have images/videos generated and to be analyzed, and collect dataset(s) (e.g., publicly available ones, or from your own research)
  - Formulate the problem(s): e.g., input-output mapping, target platforms (edge device or workstation/server), evaluation metrics
  - Find a few references in top-tier conferences/journals
  - Our goal: to have a submission ready by the end of this class, through customized project 1-3 design
- Thrust II: If no specific domains of interest,
  - Check https://paperswithcode.com/
  - Find problem(s) that interest you
  - Survey SOTA methods therein
  - Our goal: to have a submission to top-tier CV conference ready by the end of this class, through customized project 1-3 design
- Thrust III: If both do not work for you
  - We will have standard project assignments.

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Instructions and Notes

- *How to submit your solutions*: put your report (word or pdf) and results images (.png) if had in a folder named [your_unityid]_hw01 (e.g., twu19_hw01), and then compress it as a zip file (e.g., twu19_hw01.zip). Submit the zip file through **moodle**.
- *If you miss the deadline and still have unused late days, please send your zip file to TAs and me.*
  - 5 free late days (counted using 0.5 unit, <=6 hours as 0.5 late day, otherwise 1 later day) in total – use them in your ways; Afterwards, 25% off per day late**;** **Not** accepted after 3 late days per HW and Project. Not applicable to the final project.
- **Important Note**: We will **NOT** accept any replacement of submission after deadline ([+late days you use]), even if you can show the time stamp of the replacement is earlier than the deadline. So, **please double-check whether you submit correct files**.

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Project 03

- Project 03: 30%
  - Requirement:
    - final write-up (15%) and
    - self-contained reproducible code (15%): if your code is not reproducible, you will loose 10%; So, please make sure what you report in the write-up are consistent with the code.
  - Bonus points: 5
    - For novel ideas (including novel implementation of some existing techniques, e.g., in a significantly faster way under fair comparisons).
    - If you want to claim this, please add a **section 0** in your write-up to clearly present and justify **what's new. The novelty will be checked and judged by both TAs and the instructor.**

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Babysitting the training of DNN

- **Problem**: Practice the babysitting method of training neural network as discussed in Lecture notes 21-24.
  - **Step 0:** Data (you can start with existing data provided in different DL code platform, e.g., MNIST in PyTorch), and you must test your code using the face data you used in project 1 or 2.
  - **Step 1**: preprocess the data and select a data augment scheme. (Note: you can compare w/ and w/o this preprocessing step and the data-aug to see how they affect your training and testing performance)
  - **Step 2**: Choose the architecture. E.g. you can use something simple, a 3-layer FC network or the LeNet 5 (available in all deep learning platforms).
  - > Then please follow the slides (see the next slides 6 - 25). to output detailed information of this babysitting procedure.

- **Hint**: You can reuse the tutorial code in different deep learning platform (e.g., the MNIST / CIFAR10 tutorial is available in almost all platforms).
  - E.g., If you use pytorch, you can find a lot of examples at https://pytorch.org/tutorials/
- **Requirement**: Although you can reuse the tutorial code, you need to modify the code to output different babysitting information (see the next slides 4 - 23). You need to snap your screenshots and paste those in your reports as shown in the slides. You also need to provide **self-contained reproducible code** .

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Project 03 -- Babysitting the Learning Process

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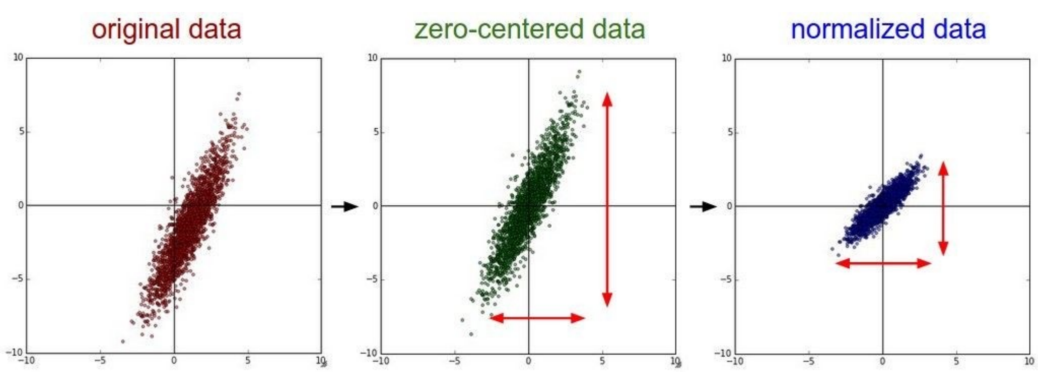
Step 1 Data Preprocessing




```
X -= np.mean(X, axis = 0)
```

```
X /= np.std(X, axis = 0)
```

(Assume X [NxD] is data matrix, each example in a row)

You can try: with and w/o data normalization

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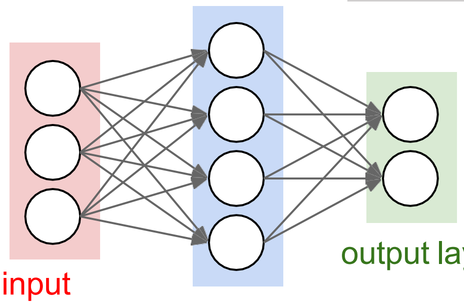
Step 2: Choose the architecture

- E.g., we start with one hidden layer of 50 neurons or LeNet or AlexNet …

50 hidden neurons

For simple FC networks like this 3-layer one, you Can code from scratch.



CIFAR-10 images, **3072** numbers

input layer

hidden layer

output layer

10 output neurons, one per class

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Double check that the loss is reasonable:

CHECK this step with your network and data

```
def init_two_layer_model(input_size, hidden_size, output_size):
  # initialize a model
  model = {}
  model['W1'] = 0.0001 * np.random.randn(input_size, hidden_size)
  model['b1'] = np.zeros(hidden_size)
  model['W2'] = 0.0001 * np.random.randn(hidden_size, output_size)
  model['b2'] = np.zeros(output_size)
  return model
```

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
loss, grad = two_layer_net(X_train, model, y_train, 0.0)
print loss
```

```
2.30261216167
```

disable regularization

loss ~2.3. “correct” for 10 classes

returns the loss and the gradient for all parameters

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Double check that the loss is reasonable:

```
def init_two_layer_model(input_size, hidden_size, output_size):
  # initialize a model
  model = {}
  model['W1'] = 0.0001 * np.random.randn(input_size, hidden_size)
  model['b1'] = np.zeros(hidden_size)
  model['W2'] = 0.0001 * np.random.randn(hidden_size, output_size)
  model['b2'] = np.zeros(output_size)
  return model
```

```
model = init_two_layer_model(32*32*3, 50, 10) # input_size, hidden_size, number of classes
loss, grad = two_layer_net(X_train, model, y_train, 1e3)
print loss
```

crank up regularization

CHECK this step with your network and data

```
3.06859716482
```

loss went up, good. (sanity check)

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Lets try to train now…

Tip: Make sure that you can overfit very small portion of the training data

```
model = init_two_layer_model(32*32*3, 50, 10) # input_size, hidden_size, number of classes
trainer = ClassifierTrainer()
X_tiny = X_train[:20] # take 20 examples
y_tiny = y_train[:20]
best_model, stats = trainer.train(X_tiny, y_tiny, X_tiny, y_tiny,
                                  model, two_layer_net,
                                  num_epochs=200, reg=0.0,
                                  update='sgd', learning_rate_decay=1,
                                  sample_batches = False,
                                  learning_rate=1e-3, verbose=True)
```

CHECK this step with your network and data

The above code:

- take the first 20 examples from CIFAR-10
- turn off regularization (reg = 0.0)
- use simple vanilla 'sgd'

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Lets try to train now…

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
trainer = ClassifierTrainer()
X_tiny = X_train[:20] # take 20 examples
y_tiny = y_train[:20]
best_model, stats = trainer.train(X_tiny, y_tiny, X_tiny, y_tiny,
                                  model, two_layer_net,
                                  num_epochs=200, reg=0.0,
                                  update='sgd', learning_rate_decay=1,
                                  sample_batches = False,
                                  learning_rate=1e-3, verbose=True)
```

Tip: Make sure that you can overfit very small portion of the training data

```
Finished epoch 1 / 200: cost 2.302603, train: 0.400000, val 0.400000, lr 1.000000e-03
Finished epoch 2 / 200: cost 2.302258, train: 0.450000, val 0.450000, lr 1.000000e-03
Finished epoch 3 / 200: cost 2.301849, train: 0.600000, val 0.600000, lr 1.000000e-03
Finished epoch 4 / 200: cost 2.301196, train: 0.650000, val 0.650000, lr 1.000000e-03
Finished epoch 5 / 200: cost 2.300044, train: 0.650000, val 0.650000, lr 1.000000e-03
Finished epoch 6 / 200: cost 2.297864, train: 0.550000, val 0.550000, lr 1.000000e-03
Finished epoch 7 / 200: cost 2.293595, train: 0.600000, val 0.600000, lr 1.000000e-03
Finished epoch 8 / 200: cost 2.285096, train: 0.550000, val 0.550000, lr 1.000000e-03
Finished epoch 9 / 200: cost 2.268094, train: 0.550000, val 0.550000, lr 1.000000e-03
Finished epoch 10 / 200: cost 2.234787, train: 0.500000, val 0.500000, lr 1.000000e-03
Finished epoch 11 / 200: cost 2.173187, train: 0.500000, val 0.500000, lr 1.000000e-03
Finished epoch 12 / 200: cost 2.076862, train: 0.500000, val 0.500000, lr 1.000000e-03
Finished epoch 13 / 200: cost 1.974090, train: 0.400000, val 0.400000, lr 1.000000e-03
Finished epoch 14 / 200: cost 1.895885, train: 0.400000, val 0.400000, lr 1.000000e-03
Finished epoch 15 / 200: cost 1.820876, train: 0.450000, val 0.450000, lr 1.000000e-03
Finished epoch 16 / 200: cost 1.737430, train: 0.450000, val 0.450000, lr 1.000000e-03
Finished epoch 17 / 200: cost 1.642356, train: 0.500000, val 0.500000, lr 1.000000e-03
Finished epoch 18 / 200: cost 1.535239, train: 0.600000, val 0.600000, lr 1.000000e-03
Finished epoch 19 / 200: cost 1.421527, train: 0.600000, val 0.600000, lr 1.000000e-03
```

Very small loss, train accuracy 1.00, nice!

```
Finished epoch 195 / 200: cost 0.002694, train: 1.000000, val 1.000000, lr 1.000000e-03
Finished epoch 196 / 200: cost 0.002674, train: 1.000000, val 1.000000, lr 1.000000e-03
Finished epoch 197 / 200: cost 0.002655, train: 1.000000, val 1.000000, lr 1.000000e-03
Finished epoch 198 / 200: cost 0.002635, train: 1.000000, val 1.000000, lr 1.000000e-03
Finished epoch 199 / 200: cost 0.002617, train: 1.000000, val 1.000000, lr 1.000000e-03
Finished epoch 200 / 200: cost 0.002597, train: 1.000000, val 1.000000, lr 1.000000e-03
finished optimization. best validation accuracy: 1.000000
```

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Lets try to train now…

Start with small regularization and find learning rate that makes the loss go down.

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
trainer = ClassifierTrainer()
best_model, stats = trainer.train(X_train, y_train, X_val, y_val,
                                  model, two_layer_net,
                                  num_epochs=10, reg=0.000001,
                                  update='sgd', learning_rate_decay=1,
                                  sample_batches = True,
                                  learning_rate=1e-6, verbose=True)
```

```
Finished epoch 1 / 10: cost 2.302576, train: 0.080000, val 0.103000, lr 1.000000e-06
Finished epoch 2 / 10: cost 2.302582, train: 0.121000, val 0.124000, lr 1.000000e-06
Finished epoch 3 / 10: cost 2.302558, train: 0.119000, val 0.138000, lr 1.000000e-06
Finished epoch 4 / 10: cost 2.302519, train: 0.127000, val 0.151000, lr 1.000000e-06
Finished epoch 5 / 10: cost 2.302517, train: 0.158000, val 0.171000, lr 1.000000e-06
Finished epoch 6 / 10: cost 2.302518, train: 0.179000, val 0.172000, lr 1.000000e-06
Finished epoch 7 / 10: cost 2.302466, train: 0.180000, val 0.176000, lr 1.000000e-06
Finished epoch 8 / 10: cost 2.302452, train: 0.175000, val 0.185000, lr 1.000000e-06
Finished epoch 9 / 10: cost 2.302459, train: 0.206000, val 0.192000, lr 1.000000e-06
Finished epoch 10 / 10: cost 2.302420, train: 0.190000, val 0.192000, lr 1.000000e-06
finished optimization. best validation accuracy: 0.192000
```

CHECK this step with your network and data

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Lets try to train now…

Start with small regularization and find learning rate that makes the loss go down.

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
trainer = ClassifierTrainer()
best_model, stats = trainer.train(X_train, y_train, X_val, y_val,
                                  model, two_layer_net,
                                  num_epochs=10, reg=0.000001,
                                  update='sgd', learning_rate_decay=1,
                                  sample_batches = True,
                                  learning_rate=1e-6, verbose=True)
```

```
Finished epoch 1 / 10: cost 2.302576, train: 0.080000, val 0.103000, lr 1.000000e-06
Finished epoch 2 / 10: cost 2.302582, train: 0.121000, val 0.124000, lr 1.000000e-06
Finished epoch 3 / 10: cost 2.302558, train: 0.119000, val 0.138000, lr 1.000000e-06
Finished epoch 4 / 10: cost 2.302519, train: 0.127000, val 0.151000, lr 1.000000e-06
Finished epoch 5 / 10: cost 2.302517, train: 0.158000, val 0.171000, lr 1.000000e-06
Finished epoch 6 / 10: cost 2.302518, train: 0.179000, val 0.172000, lr 1.000000e-06
Finished epoch 7 / 10: cost 2.302466, train: 0.180000, val 0.176000, lr 1.000000e-06
Finished epoch 8 / 10: cost 2.302452, train: 0.175000, val 0.185000, lr 1.000000e-06
Finished epoch 9 / 10: cost 2.302459, train: 0.206000, val 0.192000, lr 1.000000e-06
Finished epoch 10 / 10: cost 2.302420, train: 0.190000, val 0.192000, lr 1.000000e-06
finished optimization. best validation accuracy: 0.192000
```

Loss barely changing

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Lets try to train now…

Start with small regularization and find learning rate that makes the loss go down.

loss not going down: learning rate too low

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
trainer = ClassifierTrainer()
best_model, stats = trainer.train(X_train, y_train, X_val, y_val,
                                  model, two_layer_net,
                                  num_epochs=10, reg=0.000001,
                                  update='sgd', learning_rate_decay=1,
                                  sample_batches = True,
                                  learning_rate=1e-6, verbose=True)
```

```
Finished epoch 1 / 10: cost 2.302576, train: 0.080000, val 0.103000, lr 1.000000e-06
Finished epoch 2 / 10: cost 2.302582, train: 0.121000, val 0.124000, lr 1.000000e-06
Finished epoch 3 / 10: cost 2.302558, train: 0.119000, val 0.138000, lr 1.000000e-06
Finished epoch 4 / 10: cost 2.302519, train: 0.127000, val 0.151000, lr 1.000000e-06
Finished epoch 5 / 10: cost 2.302517, train: 0.158000, val 0.171000, lr 1.000000e-06
Finished epoch 6 / 10: cost 2.302518, train: 0.179000, val 0.172000, lr 1.000000e-06
Finished epoch 7 / 10: cost 2.302466, train: 0.180000, val 0.176000, lr 1.000000e-06
Finished epoch 8 / 10: cost 2.302452, train: 0.175000, val 0.185000, lr 1.000000e-06
Finished epoch 9 / 10: cost 2.302459, train: 0.206000, val 0.192000, lr 1.000000e-06
Finished epoch 10 / 10: cost 2.302420, train: 0.190000, val 0.192000, lr 1.000000e-06
finished optimization. best validation accuracy: 0.192000
```

Loss barely changing: Learning rate is probably too low

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Lets try to train now…

Start with small regularization and find learning rate that makes the loss go down.

loss not going down:
learning rate too low

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
trainer = ClassifierTrainer()
best_model, stats = trainer.train(X_train, y_train, X_val, y_val,
                                  model, two_layer_net,
                                  num_epochs=10, reg=0.000001,
                                  update='sgd', learning_rate_decay=1,
                                  sample_batches = True,
                                  learning_rate=1e-6, verbose=True)
```

```
Finished epoch 1 / 10: cost 2.302576, train: 0.080000, val 0.103000, lr 1.000000e-06
Finished epoch 2 / 10: cost 2.302582, train: 0.121000, val 0.124000, lr 1.000000e-06
Finished epoch 3 / 10: cost 2.302558, train: 0.119000, val 0.138000, lr 1.000000e-06
Finished epoch 4 / 10: cost 2.302519, train: 0.127000, val 0.151000, lr 1.000000e-06
Finished epoch 5 / 10: cost 2.302517, train: 0.158000, val 0.171000, lr 1.000000e-06
Finished epoch 6 / 10: cost 2.302518, train: 0.179000, val 0.172000, lr 1.000000e-06
Finished epoch 7 / 10: cost 2.302466, train: 0.180000, val 0.176000, lr 1.000000e-06
Finished epoch 8 / 10: cost 2.302452, train: 0.175000, val 0.185000, lr 1.000000e-06
Finished epoch 9 / 10: cost 2.302459, train: 0.206000, val 0.192000, lr 1.000000e-06
Finished epoch 10 / 10: cost 2.302420, train: 0.190000, val 0.192000, lr 1.000000e-06
finished optimization. best validation accuracy: 0.192000
```

Loss barely changing: Learning rate is probably too low

Notice train/val accuracy goes to 20% though, what's up with that? (remember this is softmax)

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Lets try to train now…

- Start with small regularization and find learning rate that makes the loss go down.

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
trainer = ClassifierTrainer()
best_model, stats = trainer.train(X_train, y_train, X_val, y_val,
                                  model, two_layer_net,
                                  num_epochs=10, reg=0.000001,
                                  update='sgd', learning_rate_decay=1,
                                  sample_batches = True,
```

- loss not going down:
  - learning rate too low

Now let's try learning rate 1e6.

April 19, 2018

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Lets try to train now…

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
trainer = ClassifierTrainer()
best_model, stats = trainer.train(X_train, y_train, X_val, y_val,
                                  model, two_layer_net,
                                  num_epochs=10, reg=0.000001,
                                  update='sgd', learning_rate_decay=1,
                                  sample_batches = True,
                                  learning_rate=1e6, verbose=True)
/home/karpathy/cs231n/code/cs231n/classifiers/neural_net.py:50: RuntimeWarning: divide by zero encountered in log
  data_loss = -np.sum(np.log(probs[range(N), y])) / N
/home/karpathy/cs231n/code/cs231n/classifiers/neural_net.py:48: RuntimeWarning: invalid value encountered in subtract
  probs = np.exp(scores - np.max(scores, axis=1, keepdims=True))
Finished epoch 1 / 10: cost nan, train: 0.091000, val 0.087000, lr 1.000000e+06
Finished epoch 2 / 10: cost nan, train: 0.095000, val 0.087000, lr 1.000000e+06
Finished epoch 3 / 10: cost nan, train: 0.100000, val 0.087000, lr 1.000000e+06
```

Start with small regularization and find learning rate that makes the loss go down.

loss not going down:
learning rate too low
loss exploding:
learning rate too high

cost: NaN almost always means high learning rate...

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Lets try to train now…

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
trainer = ClassifierTrainer()
best_model, stats = trainer.train(X_train, y_train, X_val, y_val,
                                  model, two_layer_net,
                                  num_epochs=10, reg=0.000001,
                                  update='sgd', learning_rate_decay=1,
                                  sample_batches = True,
                                  learning_rate=3e-3, verbose=True)

Finished epoch 1 / 10: cost 2.186654, train: 0.308000, val 0.306000, lr 3.000000e-03
Finished epoch 2 / 10: cost 2.176230, train: 0.330000, val 0.350000, lr 3.000000e-03
Finished epoch 3 / 10: cost 1.942257, train: 0.376000, val 0.352000, lr 3.000000e-03
Finished epoch 4 / 10: cost 1.827868, train: 0.329000, val 0.310000, lr 3.000000e-03
Finished epoch 5 / 10: cost inf, train: 0.128000, val 0.128000, lr 3.000000e-03
Finished epoch 6 / 10: cost inf, train: 0.144000, val 0.147000, lr 3.000000e-03
```

Start with small regularization and find learning rate that makes the loss go down.

loss not going down:
learning rate too low
loss exploding:
learning rate too high

3e-3 is still too high. Cost explodes….

=> Rough range for learning rate we should be cross-validating is somewhere [1e-3 … 1e-5]

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Hyperparameter Optimization

CHECK this step (weight decay, learning rate) with your network and data, as well as other hyperparameters which you observe to be sensitive in your training.

Cross-validation strategy

coarse -> fine cross-validation in stages

First stage: only a few epochs to get rough idea of what params work
Second stage: longer running time, finer search
… (repeat as necessary)

Tip for detecting explosions in the solver:
If the cost is ever > 3 * original cost, break out early

For example: run coarse search for 5 epochs

```
max_count = 100
for count in xrange(max_count):
      reg = 10**uniform(-5, 5)
      lr = 10**uniform(-3, -6)

      trainer = ClassifierTrainer()
      model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
      trainer = ClassifierTrainer()
      best_model_local, stats = trainer.train(X_train, y_train, X_val, y_val,
                                   model, two_layer_net,
                                   num_epochs=5, reg=reg,
                                   update='momentum', learning_rate_decay=0.9,
                                   sample_batches = True, batch_size = 100,
                                   learning_rate=lr, verbose=False)
```

note it's best to optimize in log space!

nice

```
val_acc: 0.412000, lr: 1.405206e-04, reg: 4.793564e-01, (1 / 100)
val_acc: 0.214000, lr: 7.231888e-06, reg: 2.321281e-04, (2 / 100)
val_acc: 0.208000, lr: 2.119571e-06, reg: 8.011857e+01, (3 / 100)
val_acc: 0.196000, lr: 1.551131e-05, reg: 4.374936e-05, (4 / 100)
val_acc: 0.079000, lr: 1.753300e-05, reg: 1.200424e+03, (5 / 100)
val_acc: 0.223000, lr: 4.215128e-05, reg: 4.196174e+01, (6 / 100)
val_acc: 0.441000, lr: 1.750259e-04, reg: 2.110807e-04, (7 / 100)
val_acc: 0.241000, lr: 6.749231e-05, reg: 4.226413e+01, (8 / 100)
val_acc: 0.482000, lr: 4.296863e-04, reg: 6.642555e-01, (9 / 100)
val_acc: 0.079000, lr: 5.401602e-06, reg: 1.599828e+04, (10 / 100)
val_acc: 0.154000, lr: 1.618508e-06, reg: 4.925252e-01, (11 / 100)
```

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Now run finer search...

```
max_count = 100
for count in xrange(max_count):
      reg = 10**uniform(-5, 5)
      lr = 10**uniform(-3, -6)
```

adjust range

```
max_count = 100
for count in xrange(max_count):
      reg = 10**uniform(-4, 0)
      lr = 10**uniform(-3, -4)
```

```
val_acc: 0.527000, lr: 5.340517e-04, reg: 4.097824e-01, (0 / 100)
val_acc: 0.492000, lr: 2.279484e-04, reg: 9.991345e-04, (1 / 100)
val_acc: 0.512000, lr: 8.680827e-04, reg: 1.349727e-02, (2 / 100)
val_acc: 0.461000, lr: 1.028377e-04, reg: 1.220193e-02, (3 / 100)
val_acc: 0.460000, lr: 1.113730e-04, reg: 5.244309e-02, (4 / 100)
val_acc: 0.498000, lr: 9.477776e-04, reg: 2.001293e-03, (5 / 100)
val_acc: 0.469000, lr: 1.484369e-04, reg: 4.328313e-01, (6 / 100)
val_acc: 0.522000, lr: 5.586261e-04, reg: 2.312685e-04, (7 / 100)
val_acc: 0.530000, lr: 5.808183e-04, reg: 8.259964e-02, (8 / 100)
val_acc: 0.489000, lr: 1.979168e-04, reg: 1.010889e-04, (9 / 100)
val_acc: 0.490000, lr: 2.036031e-04, reg: 2.406271e-03, (10 / 100)
val_acc: 0.475000, lr: 2.021162e-04, reg: 2.287807e-01, (11 / 100)
val_acc: 0.460000, lr: 1.135527e-04, reg: 3.905040e-02, (12 / 100)
val_acc: 0.515000, lr: 6.947668e-04, reg: 1.562808e-02, (13 / 100)
val_acc: 0.531000, lr: 9.471549e-04, reg: 1.433895e-03, (14 / 100)
val_acc: 0.509000, lr: 3.140888e-04, reg: 2.857518e-01, (15 / 100)
val_acc: 0.514000, lr: 6.438349e-04, reg: 3.033781e-01, (16 / 100)
val_acc: 0.502000, lr: 3.921784e-04, reg: 2.707126e-04, (17 / 100)
val_acc: 0.509000, lr: 9.752279e-04, reg: 2.850865e-03, (18 / 100)
val_acc: 0.500000, lr: 2.412048e-04, reg: 4.997821e-04, (19 / 100)
val_acc: 0.466000, lr: 1.319314e-04, reg: 1.189915e-02, (20 / 100)
val_acc: 0.516000, lr: 8.039527e-04, reg: 1.528291e-02, (21 / 100)
```

53% - relatively good for a 2-layer neural net with 50 hidden neurons.

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Now run finer search...

```
max_count = 100
for count in xrange(max_count):
      reg = 10**uniform(-5, 5)
      lr = 10**uniform(-3, -6)
```

adjust range

```
max_count = 100
for count in xrange(max_count):
      reg = 10**uniform(-4, 0)
      lr = 10**uniform(-3, -4)
```

```
val_acc: 0.527000, lr: 5.340517e-04, reg: 4.097824e-01, (0 / 100)
val_acc: 0.492000, lr: 2.279484e-04, reg: 9.991345e-04, (1 / 100)
val_acc: 0.512000, lr: 8.680827e-04, reg: 1.349727e-02, (2 / 100)
val_acc: 0.461000, lr: 1.028377e-04, reg: 1.220193e-02, (3 / 100)
val_acc: 0.460000, lr: 1.113730e-04, reg: 5.244309e-02, (4 / 100)
val_acc: 0.498000, lr: 9.477776e-04, reg: 2.001293e-03, (5 / 100)
val_acc: 0.469000, lr: 1.484369e-04, reg: 4.328313e-01, (6 / 100)
val_acc: 0.522000, lr: 5.586261e-04, reg: 2.312685e-04, (7 / 100)
val_acc: 0.530000, lr: 5.808183e-04, reg: 8.259964e-02, (8 / 100)
val_acc: 0.489000, lr: 1.979168e-04, reg: 1.010889e-04, (9 / 100)
val_acc: 0.490000, lr: 2.036031e-04, reg: 2.406271e-03, (10 / 100)
val_acc: 0.475000, lr: 2.021162e-04, reg: 2.287807e-01, (11 / 100)
val_acc: 0.460000, lr: 1.135527e-04, reg: 3.905040e-02, (12 / 100)
val_acc: 0.515000, lr: 6.947668e-04, reg: 1.562808e-02, (13 / 100)
val_acc: 0.531000, lr: 9.471549e-04, reg: 1.433895e-03, (14 / 100)
val_acc: 0.509000, lr: 3.140888e-04, reg: 2.857518e-01, (15 / 100)
val_acc: 0.514000, lr: 6.438349e-04, reg: 3.033781e-01, (16 / 100)
val_acc: 0.502000, lr: 3.921784e-04, reg: 2.707126e-04, (17 / 100)
val_acc: 0.509000, lr: 9.752279e-04, reg: 2.850865e-03, (18 / 100)
val_acc: 0.500000, lr: 2.412048e-04, reg: 4.997821e-04, (19 / 100)
val_acc: 0.466000, lr: 1.319314e-04, reg: 1.189915e-02, (20 / 100)
val_acc: 0.516000, lr: 8.039527e-04, reg: 1.528291e-02, (21 / 100)
```

53% - relatively good for a 2-layer neural net with 50 hidden neurons.

But this best cross-validation result is worrying. Why?

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Summary

- Activation Functions (use ReLU)
- Data Preprocessing (images: subtract mean, divide std)
- Weight Initialization (use Xavier/He init)
- Batch Normalization (use)
- Babysitting the training process

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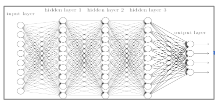
[Optional] Bonus Points for Creativity and Novelty

- Exploring new designs in, but not limited to, three aspects as follows.



- "Representation": the space of neural architectures (*going deeper and/or wider*) → LeNet5, AlexNets, GoogLeNets, ResNets, ResNeXts, DenseNets, DualPathNets, and AOGNets, etc.
- "Representation": the space of operations → vanilla conv., depthwise conv., separable conv., Atrous conv., deformable conv., different variants of ReLU, etc.
- "Learning": the space of parameters → Initialization, Normalization, Pre-training,etc.
- "Learning": the space of regularizer → Data augmentation (appearance and geometry transformation), DropOut, Weight Decay, etc

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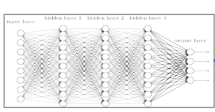
Bonus Points for Creativity and Novelty

- Potential Topic 1: New design of network architectures



"Representation": the space of neural architectures (*going deeper and/or wider*) → LeNet5, AlexNets, GoogLeNets, ResNets, ResNeXts, DenseNets, DualPathNets, and AOGNets, etc.

- Understand existing neural architectures
- Be critical and creative to think about different designs
  - Exploring the space of DAGs for network topologies.
  - E.g., exploiting your background domain knowledge, if you work in the circuit design field, or if you are familiar with molecular structures in chemistry or fluid dynamics in physics or theoretical studies of DAGs in mathematics, you can leverage different principles of designing efficient and effective "information flows" in those fields. **[Be creative!]**
  - Some baselines: you can think about how to combine different existing designs together.
- Validate your ideas on CIFAR10 (and/or CIFAR100)
- If your ideas are very promising, I will try to help you test on ImageNet using a large GPU server.
  - If the results are good, we can submit to computer vision/AI conferences.

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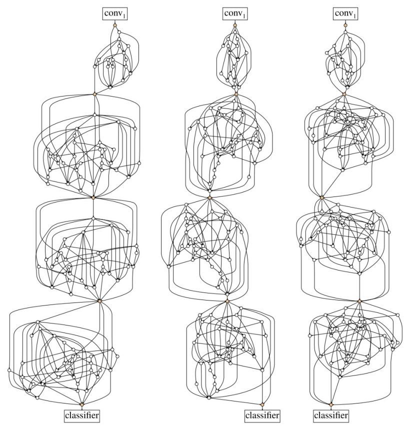
Bonus Points for Creativity and Novelty

- Potential Topic 1: New design of network architectures
- Examples to inspire you

Exploring Randomly Wired Neural Networks for Image Recognition

Saining Xie Alexander Kirillov Ross Girshick Kaiming He
Facebook AI Research (FAIR)

Google and Read the paper



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Bonus Points for Creativity and Novelty

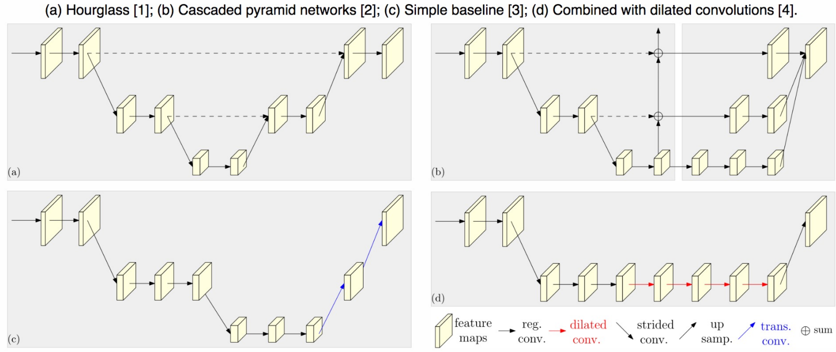
- Potential Topic 1: New design of network architectures
- Examples to inspire you

Deep High-Resolution Representation Learning for Human Pose Estimation

Ke Sun Bin Xiao Dong Liu Jingdong Wang

Google and Read the paper

(a) Hourglass [1]; (b) Cascaded pyramid networks [2]; (c) Simple baseline [3]; (d) Combined with dilated convolutions [4].



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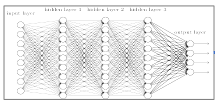
Bonus Points for Creativity and Novelty

- Potential Topic 2: New design of node operations



"Representation": the space of operations → vanilla conv., depthwise conv., separable conv., Atrous conv., deformable conv., different variants of ReLU, etc.

- Understand existing operations
- Be critical and creative to think about different designs
  - Consider existing network architectures such as ResNets or DenseNets (PyTorch has default implementation), and how to extend their operations (e.g., they use the Bottleneck operation)
  - Exploring the combinations of different primitive operations using some micro-topologies similar in the spirit to network-in-network (https://arxiv.org/abs/1312.4400).
  - Examples (understand how they improved the existing networks):
    - SENet: https://arxiv.org/abs/1709.01507
    - Non-local networks: https://arxiv.org/abs/1711.07971 https://arxiv.org/abs/1811.11721
    - Image Transformer: https://arxiv.org/abs/1802.05751
    - HetConv https://arxiv.org/pdf/1903.04120.pdf
  - Exploiting your background domain knowledge on methods of how to explore spatial and channel contextual information, or attention mechanism for operation design. **[Be creative!]**
- Validate your ideas on CIFAR10 (and/or CIFAR100)
- If your ideas are very promising, I will try to help you test on ImageNet or other big datasets using a large GPU server.
  - If the results are good, we can submit to computer vision/AI conferences.

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Bonus Points for Creativity and Novelty

- Potential Topic 2: New design of node operations
- Examples to inspire you

Res2Net: A New Multi-scale Backbone Architecture

Shang-Hua Gao*, Ming-Ming Cheng*, Kai Zhao, Xin-Yu Zhang, Ming-Hsuan Yang, and Philip Torr

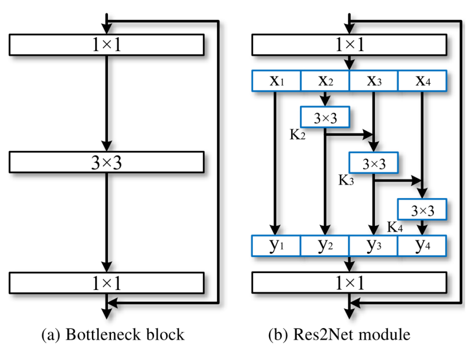

Fig. 2: Comparison between the bottleneck block and the proposed Res2Net module (the scale dimension $s = 4$).

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Bonus Points for Creativity and Novelty

- Potential Topic 2: New design of node operations
- Examples to inspire you

Drop an Octave: Reducing Spatial Redundancy in Convolutional Neural Networks with Octave Convolution

Yunpeng Chen[†‡], Haoqi Fang[†], Bing Xu[†], Zhicheng Yan[†], Yannis Kalantidis[†], Marcus Rohrbach[†], Shuicheng Yan[‡♭], Jiashi Feng[‡]
[†]Facebook AI, [‡]National University of Singapore, [♭]Qihoo 360 AI Institute

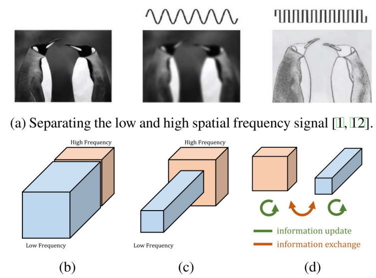

Figure 1: (a) Motivation. The spatial frequency model for vision [1, 12] shows that natural image can be decomposed into a low and a high spatial frequency part. (b) The output maps of a convolution layer can also be factorized and grouped by their spatial frequency. (c) The proposed multi-frequency feature representation stores the smoothly changing, low-frequency maps in a low-resolution tensor to reduce spatial redundancy. (d) The proposed Octave Convolution operates directly on this representation. It updates the information for each group and further enables information exchange between groups.

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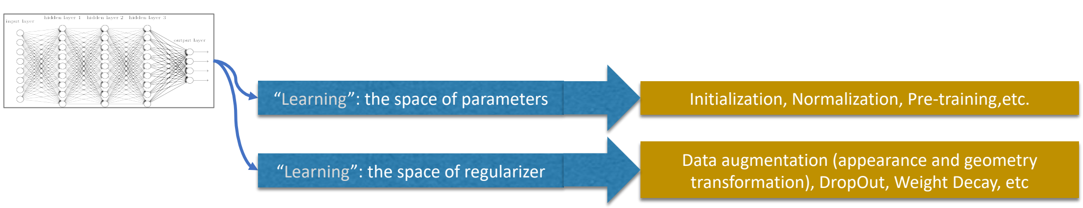
Bonus Points for Creativity and Novelty

- Potential Topic 3: New design of learning



- Understand existing initialization and normalization methods
- Be critical and creative to think about different designs
  - Consider existing network architectures such as ResNets or DenseNets (PyTorch has default implementation), and how to train them with different initialization/normalization methods
  - Examples (understand how they improved the vanilla random initialization and the vanilla BatchNorm methods):
    - https://arxiv.org/abs/1502.01852
    - Fixup: https://arxiv.org/abs/1901.09321v1
    - BatchNorm, InstanceNorm, LayerNorm and GroupNorm: https://arxiv.org/abs/1803.08494 (and related references therein)
    - How does BatchNorm work: https://arxiv.org/abs/1805.11604
    - SwitchableNorm: https://github.com/switchablenorms/Switchable-Normalization
    - Attentive Norm: https://arxiv.org/abs/1908.01259
    - Feature response norm: https://arxiv.org/pdf/1911.09737.pdf
- Validate your ideas on CIFAR10 (and/or CIFAR100)
- If your ideas very promising, I will try to help you test on ImageNet or other big datasets using a large GPU server.
  - If the results are good, we can submit to computer vision/AI conferences.

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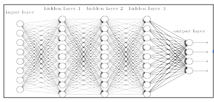
Bonus Points for Creativity and Novelty

- Potential Topic 3: New design of learning



"Learning": the space of parameters → Initialization, Normalization, Pre-training,etc.

"Learning": the space of regularizer → Data augmentation (appearance and geometry transformation), DropOut, Weight Decay, etc

- Understand existing data augmentation "tricks"
- Be critical and creative to think about different designs
  - Consider existing network architectures such as ResNets or DenseNets (PyTorch has default implementation), and how to train them with different initialization/normalization methods
  - Examples (understand how they augment the training data):
    - Cutout: https://arxiv.org/abs/1708.04552
    - Mixup: https://arxiv.org/abs/1710.09412
    - Bag of tricks: https://arxiv.org/abs/1812.01187 (and references for the tricks therein)
    - Grid Mask: https://arxiv.org/abs/2001.04086
  - Any transformation functions that do not change the task semantics are applicable. **[Be creative!]**
- Validate your ideas on CIFAR10 (and/or CIFAR100)
- If your ideas very promising, I will try to help you test on ImageNet or other big datasets using a large GPU server.
  - If the results are good, we can submit to computer vision/AI conferences.