Part C Project Notes

Catherine Vlasov

April 28, 2019

Contents

Chapter 1

Task Documentation

All timings mentioned here are approximate. The specific results can be found in Chapter 4.

1.1 Image Curation

1.1.1 Initial Image Selection

The first step was selecting which images to use for the experiments. Flickr released a massive database of millions of images and we will use those taken by one user, referred to as `actor00003`. There are $13,349$ images taken by this user and they are on the server under `/array/vlasov/actor00003`. The largest image size in this directory is 3072×2304 pixels and information about all the images is in a file called `metadata.txt` in the same directory.

I wrote a script called `initial_curation.py` to do the initial image filtering. The script uses the metadata file to identify the images that are 3072×2304 pixels, makes all of these images grayscale, rotates the portrait ones to landscape, and places the resulting images in a new subdirectory called `size3072`. The script took around 10 minutes to run and 9539 grayscale, 3072×2304 pixel, landscape images were produced.

1.1.2 Choosing Image Sizes

The largest size is 3072×2304 since that is the largest size we have from `actor00003` and the smallest size was somewhat arbitrarily chosen to be 360×240. In the graphs with my experiment results, I will want the image sizes (specifically the total number of pixels) to be evenly distributed along the x-axis. In order to achieve this, I picked sizes such that the difference between the number of pixels in consecutive image sizes is roughly the same. I calculated this interval using:

$$\frac{3072 \cdot 2304 - 320 \cdot 240}{9} \approx 777,899 \text{ pixels}$$

It is straightforward to compute the total number of pixels in the n^{th} image size (where 320×240 is the 1^{st} size and 3072×2304 is the 10^{th} size):

$$320 \cdot 240 + (n-1) \cdot 777,899$$

Given the desired number of pixels (call it P), we can find dimensions with a 4:3 ratio that produce approximately P pixels. We do so by solving the following equation for x and then computing $4x$ and $3x$ to get the dimensions:

$$P \approx 4x \cdot 3x = 12x^2$$

The results of these computations are:

Width	Height	Total pixels
3072	2304	7,077,888
2912	2184	6,359,808
2720	2040	5,548,800
2528	1896	4,793,088
2304	1728	3,981,312
2048	1536	3,145,728
1792	1344	2,408,448
1472	1104	1,625,088
1056	792	836,352
320	240	76,800

1.1.3 Cropping

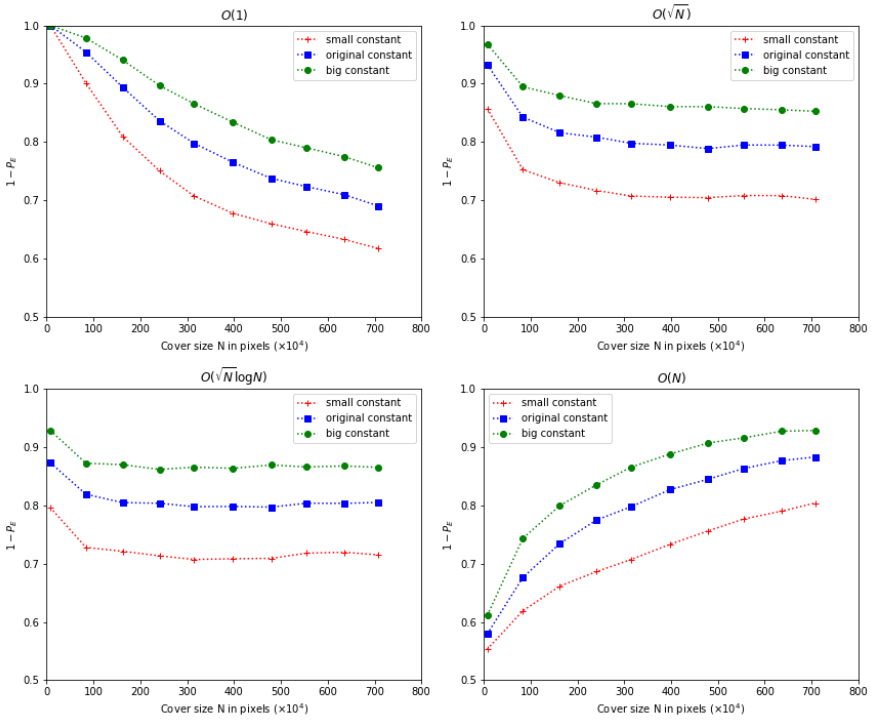
I wrote a script called `crop.py` to crop the original cover photos to the sizes computed in Section 1.1.2. It takes the desired height and width as well as source and destination directories as commandline arguments. Then it computes where the cropping should start so that 8×8 blocks are cropped evenly from the top/bottom and left/right and then runs `jpegtran` to do the cropping on all the images in the given source directory. It took around 6 minutes to crop to the smallest size (320×240) and 11 and a half minutes to crop to the second-largest size (2720×2040).

Chapter 2

Meeting Notes

2.1 Easter Break

- Complete results (from 29/03/19) with larger/smaller constants:



2.2 08/03/19

- What I did:
  - Computed two new sets of constants:

	−30%	Original	+30%
r1	49176.55272727272	70252.21818181817	91327.88363636362
r2	27.726656205965558	39.609508865665084	51.492361525364615
r3	1.2845357597929208	1.8350510854184585	2.385566411043996
r4	0.01563280510179924	0.022332578716856056	0.029032352331912873

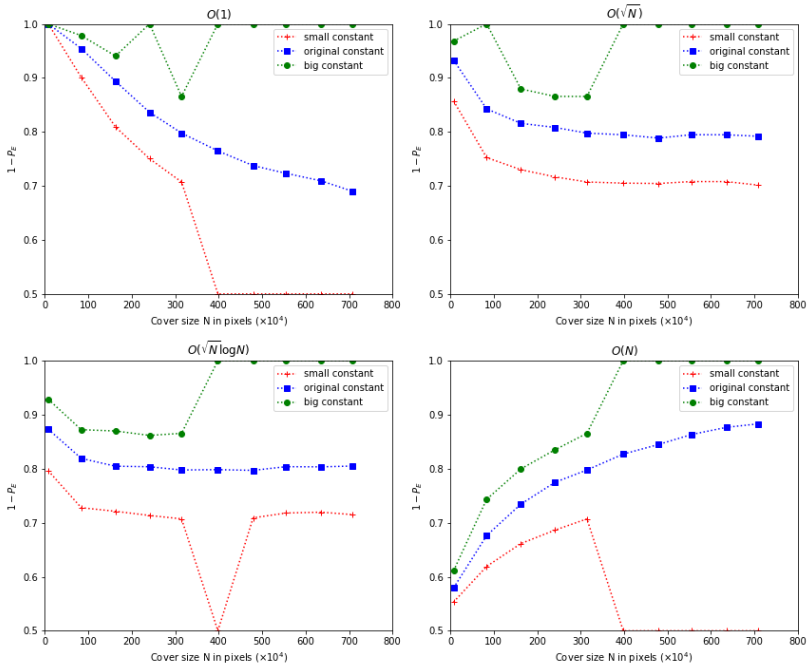
– Computed new payload sizes for the smaller constants:

Width	Height	Pixels	$O(1)$	$O(\sqrt{n})$	$O(\sqrt{n} \cdot \log n)$	$O(n)$
3072	2304	7077888	49176	73764	77762	110647
2912	2184	6359808	49176	69922	73212	99421
2720	2040	5548800	49176	65312	67790	86743
2528	1896	4793088	49176	60702	62410	74929
2304	1728	3981312	49176	55323	56194	62239
2048	1536	3145728	49176	49176	49176	49176
1792	1344	2408448	49176	43029	42261	37650
1472	1104	1625088	49176	35345	33785	25404
1056	792	836352	49176	25356	23111	13074
320	240	76800	49176	7683	5777	1200

– Computed new payload sizes for the larger constants:

Width	Height	Pixels	$O(1)$	$O(\sqrt{n})$	$O(\sqrt{n} \cdot \log n)$	$O(n)$
3072	2304	7077888	91327	136991	144416	205487
2912	2184	6359808	91327	129856	135966	184640
2720	2040	5548800	91327	121294	125895	161094
2528	1896	4793088	91327	112732	115905	139154
2304	1728	3981312	91327	102743	104361	115586
2048	1536	3145728	91327	91327	91327	91327
1792	1344	2408448	91327	79911	78485	69922
1472	1104	1625088	91327	65641	62744	47180
1056	792	836352	91327	47090	42921	24281
320	240	76800	N/A	14269	10728	2229

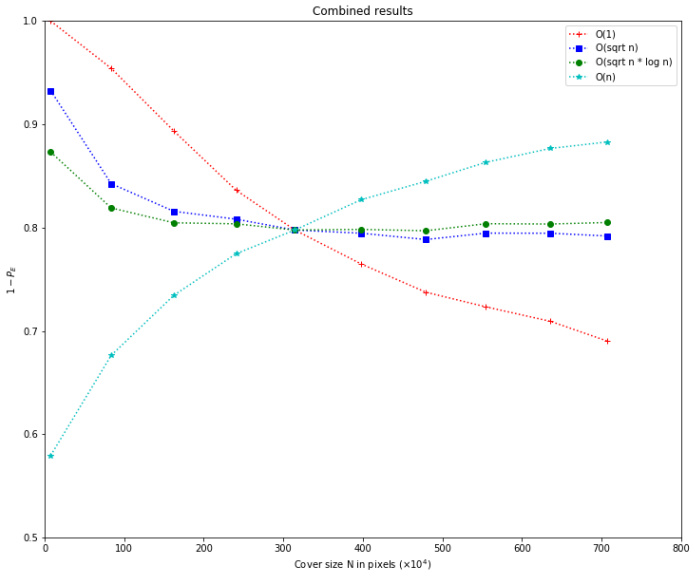
– Results (so far) of experiments using smaller and larger constants:



- My next set of experiments will be on BOSSbase.

2.3 01/03/19

- What I did:
  - Finished all experiments and put together the results graph:



– Miscellaneous:

  * I parallelised the feature computation just like with embedding by looking at the last digit of the image numbers to spin up ten concurrent processes. Before, the feature files were being computed sequentially, which took 5-10 hours (depending on the image size). Now it takes less than 30 minutes.
  * I tried using `at` for task scheduling, but realised that it means that I lose the timing information. This is because `at` either swallows the standard output/error or emails it to you, given the appropriate command line argument. But, there doesn't seem to be an appropriate email program installed and I don't know if it's worth it to use.
  * A lot of timing information for the binary embedding was lost because somehow I (or my script) didn't specify/incorrectly specified a file for redirecting the standard output when running commands with `nohup`. It was all instead written to the default `nohup.out` file, which is now a big mess because many processes were writing to it concurrently. I made a note of all the tasks for which I have not timing information in my results tables at the end of this document.
  * I made a copy of all the features into `/home` as a backup.
  * I didn't end up applying to the BCS conference because of personal matters I had to deal with last week (deadline was

Friday 22nd February) and because of uncertainty with what I was going to do over the break.
    - I just booked my flights back to Canada and I am gone from 12th March to 4th April.
    - I started adding papers to my bibliography. What format do I use? Which pieces of information are necessary (e.g. location, specific date as opposed to year)?
  - Next: do the same set of experiments but with two different constants - which ones?

- Now redo the experiment with two new sets of constants. These can be +/- 30% of the existing ones. Should result in graphs with very similar shapes, just shifted slightly upwards and downwards, respectively.

- I should also try training the classifier on all image sizes (e.g. a tenth of the images of each size) and then finding its error rate on images of each size.

- It would be good to run these experiments on another images set. Dr. Ker will dig up the BOSSBase images and I can use these next.

2.4 15/02/19

- What I did:
  - Reran `calculate_payload_sizes.py` to get the right $O(\sqrt{n} \cdot \log n)$ payload sizes (now 2048×1536 has the same payload size in all cases):

Width	Height	Pixels	$O(1)$	$O(\sqrt{n})$	$O(\sqrt{n} \cdot \log n)$	$O(n)$
3072	2304	7077888	70252	105378	111089	158067
2912	2184	6359808	70252	99889	104589	142030
2720	2040	5548800	70252	93303	96843	123919
2528	1896	4793088	70252	86717	89158	107042
2304	1728	3981312	70252	79033	80278	88912
2048	1536	3145728	70252	70252	70252	70252
1792	1344	2408448	70252	61470	60373	53786
1472	1104	1625088	70252	50493	48264	36292
1056	792	836352	70252	36223	33016	18677
320	240	76800	70252	10976	8253	1715

2.5 08/02/19

- What I did:

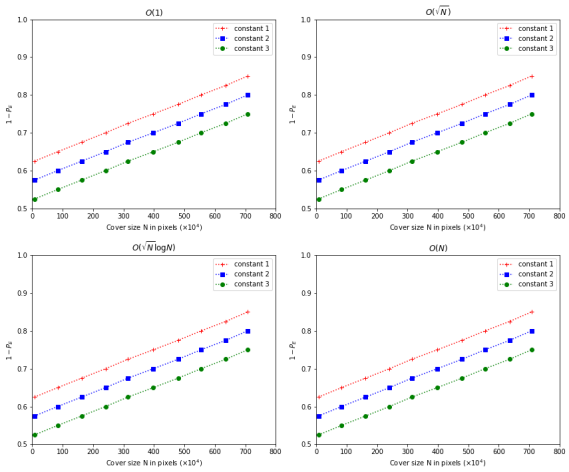
  - Fixed problems with the binary embedding code.
    * There was a problem with the exponential search for lambda getting stuck in an infinite loop. Then, I figured out that the floating point precision in the binary search for λ was insufficient for finding a value of λ such that the entropy sum is in the range $b \leq \lambda < b + 1$, where b is the number of payload bits. For $b = 70252$, it turned out that the entropy sum reached $70,253$ but could no longer be refined because the upper and lower bounds for λ had reached the limits of the floating point precision.
  - Ran binary embedding on all image sizes for the $O(\sqrt{n})$ payloads (and all payload sizes for the 320×240 images)
    * There were hangups in the middle of the embedding processes, so I killed all processes.
  - Noticed that the payload sizes computed for $O(\sqrt{n} \cdot \log n)$ are wrong because the number of bits for the middle size is different from the the number of bits for the same size but other proportions. Probably a bug in the code.

- The MinPE values for the processes that finished (only the ones for 320×240 images) look correct.

- There was indeed a bug in my `calculate_payload_sizes.py` script - I forgot to replace one of the calls to `log(x)` with `log(x,2)`, to use the right logarithm base.

2.6 25/01/19

- What I did:
  - Finished the graph template for the experiment results:



  - If we decide to use only one proportionality constant for each payload size, then we will only have one plot per figure (rather than three like in the 2008 paper).
- Finished writing the binary embedding code.
  - Not quite working. Either throws an unknown error or behaves as if there are no images to process.

2.7 11/01/19

- What I did:
  - Finished running J-UNIWARD on all remaining images sizes.
  - Picked values for r_1, r_2, r_3, r_4.
    - The image size and α combination that produced a MinPE value closest to 20% was 1056×792 with $\alpha = 0.3$ (MinPE = 22%).
    - I ran `JPEG-UTILS` on all the 1056×792 images and found that the average number of non-zero coefficients was $120,746$.
    - Since 0.3 bits per non-zero coefficient were embedded in each image, this means that an average of $0.3 \times 120,746 = 36,224$ bits were embedded per image.
    - I chose 2048×1536 to be the "middle" image size. There are ten sizes, so it was either this or 2304×1728.
    - I wrote a script `calculate_payload_sizes.py` that computes the number of bits that should be embedded for each image size for each proportion (i.e. $O(1)$, $O(\sqrt{n})$, $O(\sqrt{n} \cdot \log n)$, and $O(n)$, where n is the number of pixels in each image).

* Compute the constant values computed as intermediate values by my script are:
  - $r_1 = 70252.21818181817$
  - $r_2 = 39.609508865665084$
  - $r_3 = 2.64741910071112$
  - $r_4 = 0.022332578716856056$
  - For some reason, these values (and the values in the table below) differ when run on my computer versus on the server.
* Using these constants, compute the number of bits to embed for each image size:

Width	Height	Pixels	$O(1)$	$O(\sqrt{n})$	$O(\sqrt{n} \cdot \log n)$	$O(n)$
3072	2304	7077888	70252	105378	160268	158067
2912	2184	6359808	70252	99889	150891	142030
2720	2040	5548800	70252	93303	139714	123919
2528	1896	4793088	70252	86717	128628	107042
2304	1728	3981312	70252	79033	115816	88912
2048	1536	3145728	70252	70252	101352	70252
1792	1344	2408448	70252	61470	87100	53786
1472	1104	1625088	70252	50493	69631	36292
1056	792	836352	70252	36223	47632	18677
320	240	76800	70252	10976	11906	1715

- Later we can try training the classifier on all image sizes (maybe 10% of the images of each size) and then run it against the images of each size. It can also be run against a set of images of multiple sizes.
- Once we have the results, we can also try running all the experiments again on another set of images (from another actor).
  - Actor 27 has 4890 images shot on an iPhone, but they are very small (320×480).
  - Actor 245 has 1524 images shot on an iPhone, of various different sizes.
  - Actor 17 has a Sony camera with a good number of images and a nice camera.
  - We could also use the original BossBase images (as opposed to the ones that have been shrunken down to 512×512). But a bit overused and artificial since they come from lots of different cameras.
- YFCC100m dataset

2.8 03/12/18

- What I did:
  - Found a way to convert the features in the `imageXXXXX.fea` files into a format that the linear classifier can use.
    - Wrote `combine_feature_files.py`, which creates a single file (e.g. `sizeX_cover.fea`) with the features of all the images in a directory, one image per line. Each line is tab-separated and has the image name followed by the features (in row order).
    - Wrote `txt_to_mat.m`, which takes a combined feature file and produces a `.mat` file that MATLAB can read to get the features in fields with names (and dimensions) that it expects.
  - Ran (ternary) J-UNIWARD embedding with $\alpha = 0.1$ on the six smallest image sizes.
    - Realized that I wasn't reusing the J-UNIWARD costs I had previously computed, so I killed the processes that hadn't terminated yet (sizes $1792 \times 1344, 2048 \times 1536, 2304 \times 1728$)
  - Created a modified J-UNIWARD that reads in the pre-computed costs from the `imageX.costs` files in the cover image directory.
    - Started running this on the sizes that hadn't terminated without reusing costs.
    - Sizes $1792 \times 1344, 2048 \times 1536, 2304 \times 1728$ haven't terminated yet although they've been running for several days.
  - Ran `compute_features.py` on $J_{0.1}$ images (sizes $320 \times 240, 1056 \times 792, 1472 \times 1104$).
  - Started working on modifying J-UNIWARD to do binary embedding.

2.9 21/11/18

- What I did:
  - Wrote `feature_sanity_check.py`, which adds up all the features for each image in a directory and outputs how many had the same sum (1346, a constant) and how many had zero sum (due to no features being generated).
    - Ran it on all image sizes and found that the number of images for which the features weren't generated when I ran JRM on 10/11/18 increased as the image sizes increased.
  - Reran `compute_features.py` on all images of all sizes.

    - This time no images were skipped, which is good. However, the timing information was lost because for some reason the terminal output was not redirected to a file by `nohup`. This may have been caused by the fact that `nohup` was run by a Bash script for each file size and most likely I forgot the `&` at the end of the line. All I know is that all processes finished after around 18-20 hours. This roughly matches the timing information from the original run on 10/11/18 when some images were skipped.
    - I reran `feature_sanity_check.py` for all sizes. This confirmed that no images were skipped and that the sum of all features in each image of each size was 1346, as expected.
- Changed `compute_costs.py` so that Python's `multiprocessing` module is used for multithreading in order to spread out the cost computation over multiple processes to speed it up.
    - I initially tried using Python's `threading` module, however creating multiple threads does not actually mean the computation is run in parallel due to Python's global interpreter lock (GIL).
    - `multiprocessing`, on the other hand, avoids the limitations of the GIL and allows multiple processes (as opposed to threads) to be created and make use of multiple cores.
    - Here is a good pro/con analysis of the two modules.
- Ran `compute_costs.py` on all images of all sizes.
    - All cost files were generated, as expected.
    - The terminal output is messy due to multiple processes printing concurrently. However, the total time is clearly visible on the last line of the terminal output.
- TL;DR the costs and features of all cover images are all computed!
- Wrote my own program called `JPEG-UTILS`, which is based on the J-UNIWARD code and provides a number of checks and information about cover/stego images.
    - Currently it provides two utilities:
        1. Non-zero coefficient count: number of non-zero coefficients in a (cover) image
        2. Differing coefficients: number of coefficients that differ between cover/stego image pairs, broken down by the number that differ by +1, -1, or something else.
- Looked into how to implement my own binary embedding and it looks like there's no need to reinvent the wheel and the J-UNIWARD code can mostly be reused. Want to discuss.

- *Should I rerun the feature computations just to get the timing information? It takes 18-20 hours.*
  - I can, but it's not a priority now. I could do it later when I'm running the real experiments.
- The `float* pixel_costs` in `cost_model.cpp` of the J-UNIWARD code looks like it's initialized, filled, and then never used, but its "initialization" is actually C pointer arithmetic based on the address of the `float* costs` which is a field inherited from `base_cost_model.cpp`.
- Equations for binary versus ternary embedding
  1. Binary embedding
     - This is the probability of changing coefficient i by ± 1, where c_i is the cost of changing coefficient i (by ± 1) and $c_{\neg i} = 0$ is the cost of not changing it:

$$\pi_i = \frac{1}{1 + e^{\lambda c_i}} = \frac{1}{e^{\lambda c_{\neg i}} + e^{\lambda c_i}} = \frac{e^{-\lambda c_i}}{e^{-\lambda c_{\neg i}} + e^{-\lambda c_i}}$$

     - Entropy function for coefficient i:

$$-\pi_i \log \pi_i - (1 - \pi_i) \log(1 - \pi_i)$$

  2. Ternary embedding
     - This is the probability of changing coefficient i by $+1$ (for example), where $c_i^0 = 0$ is the cost of not changing coefficient i, c_i^{+1} is the cost of changing it by $+1$, and c_i^{-1} is the cost of changing it by -1:

$$\pi_i^{+1} = \frac{e^{-\lambda c_i^{+1}}}{1 + e^{-\lambda c_i^{+1}} + e^{-\lambda c_i^{-1}}} = \frac{e^{-\lambda c_i^{+1}}}{e^{-\lambda c_i^{0}} + e^{-\lambda c_i^{+1}} + e^{-\lambda c_i^{-1}}}$$

       * In practice, $c_i^{+1} = c_i^{-1} (= C$, say) for all i, meaning that the costs of adding one versus substracting one are the same, so:

$$\pi_i^{+1} = \pi_i^{-1} = \frac{e^{-\lambda C}}{1 + 2 \cdot e^{-\lambda C}}$$

     - Entropy function for coefficient i:

$$-\pi_i^{+1} \log \pi_i^{+1} - \pi_i^{-1} \log \pi_i^{-1} - \pi_i^{0} \log \pi_i^{0}$$

- *Can I reuse the structure of the J-UNIWARD code to implement binary embedding?*

  - Yes, but I need to be careful to make sure things are read in the right order and all methods whose implementations are specifically for ternary embedding are adapted to be for binary embedding.
  - Specifically, the entropy function and probability computation need to be changed to use the equations described in the point above.
  - I also need to adapt it so that it takes a number of bits as an argument instead of the number of bits per non-zero coefficient.

- The JRM paper describes how JRM produces 22,510 features. These are actually made up of two sets of 11,255 features, one for the image itself and one for the same image, but with 4-pixel strips cropped off all sides ("Cartesian calibration").

  - The reason the features all add up to the same constant for each image, regardless of size, is that the features are normalized so that they sum to 1. The way JRM computes the features is based on "submodels" and all images have the same number of submodels (672) regardless of size.
  - The features within each submodel (something like this) are normalized, so summing all the features of both halves (from the two versions of the image), makes a total sum of $672 \cdot 1 + 672 \cdot 1 = 1346$, which is what we get when running `feature_sanity_check.py`.

- When I run J-UNIWARD for the pre-experiments, I should actually use 0.1 instead of 0.4 as previously discussed.

  - For BOSSbase, where all images are 512×512, $\alpha = 0.2$ produced a "good" classification error rate. However, those images are about $\frac{1}{4}$ of a megapixel whereas the middle size images in our dataset are about 3 megapixels.

- Step-by-step explanation of how we'll choose constants $r_1, ..., r_4$ in order to compute the number of bits of payload to embed. Goal: pick them such that $r_1 = r_2 \cdot \sqrt{n_{mid}} = r_3 \cdot \sqrt{n_{mid}} \cdot \log n_{mid} = r_4 \cdot n_{mid}$, where n_{mid} is the number of pixels in the "middle" image size.

  1. Run J-UNIWARD with $\alpha = 0.1$ on some of the image sizes (among the smaller half of the sizes).
  2. Compute the features of these stego images and then train and run the classifier on these cover-stego image pairs.
  3. Record the classifier's error rate (call it P_e) for each image size.

4. We want to find an image size where $P_e \approx 20\%$. Using `JPEG-UTILS`, see how many non-zero coefficients there were on average and then use this and $\alpha = 0.1$ to compute the average number of bits that were embedded (well, simulated).
5. Assuming the square root law holds, pro-rate this to compute the number of bits that should be embedded in the middle image size. Call this m^*_{mid}.
6. Knowing m^*_{mid} and n_{mid}, compute $r_1, ..., r_4$ so that:

$$\begin{aligned} m^*_{mid} &= r_1 \\ m^*_{mid} &= r_2 \cdot \sqrt{n_{mid}} \\ m^*_{mid} &= r_3 \cdot \sqrt{n_{mid}} \cdot \log n_{mid} \\ m^*_{mid} &= r_4 \cdot n_{mid} \end{aligned}$$

- 95% confidence interval formula (where P is the error rate and n is the sample size):

$$\pm 1.96 \cdot \sqrt{\frac{P \cdot (1 - P)}{n}}$$

- We don't need to worry about splitting the data into training, validation, and testing sets. We can let the classifier handle it using its default behaviour. We're not too concerned about doing "perfect" machine learning since we can't get many significant figures in our rates in a statistically significant way given that we only have 10,000 images.

2.10 14/11/18

- What I did:
  - Ran the hacked J-UNIWARD to compute the costs of all the images of all sizes.
    - It computed the costs of all the 320×240 images after about 2 hours, but the processes computing the costs for the other sizes either terminated in the middle of their execution (before finishing all images), or did not terminate at all (in the case of 2912×2184 and 2720×2040) althought they were not making any progress.
  - Wrote `compute_features.py`, which runs JRM on all the JPEGs in a directory and saves the results to a `.fea` file.
  - Ran `compute_features.py` on all images of all sizes.
    - All ten processes terminated and processed all images.
    - The slowest one took 1h22m and the longest one took 20h4m.

    - However, some of the `.fea` files generated were empty and I don't know why.
  - Was sick the last week, so didn't get much else done.

- The timing of me running J-UNIWARD and JRM (in parallel) coincided with some issues on the server with regard to memory.
  - It ended up being restarted, so I should just rerun everything.
  - Apparently, JRM does sometimes silently fail. However, when I reran it on some of the images whose features were not computed, it worked which was odd.

- It's possible that there was an issue with the simultaneous cost and feature computations because the `compute_features.py` iterated through all files in the directory while more files were being generated both by itself and by J-UNIWARD.
  - When rerunning the computations, I'll modify my script to iterate from 1 to 13349 to "create" the image names itself (and check that they actually exist, since not all 13349 images were used), which will avoid any issues with simultaneous directory iteration and file generation.

- The sums of the features of each image should be a constant, so it would be a good idea to do a sanity check to ensure that this is indeed the case.

- To make the cost and feature computations go faster, it would be a good idea to spin off multiple threads (in Python).
  - For instance, I could spin off 10 threads and make thread 1 handle images with number 1 (mod 10).

- Before running experiments, we need to choose constants $r_1, ..., r_4$ in order to compute the number of bits of payload to embed.
  - Amounts: $r_1, r_2 \cdot \sqrt{n}, r_3 \cdot \sqrt{n} \cdot \log n, r_4 \cdot n$ for each # of pixels n.
  - To choose $r_1, ..., r_4$, we do the following:
    1. Run J-UNIWARD with 0.4 bits per non-zero coefficient for all (or every other) image size.
    2. Write and run a script that counts the number of coefficients that differ between the cover and stego images.
    3. From those counts, compute the number of bits that were embedded for each size.
    4. Compute the features of the stego images.

5. Train the classifier with the features of the cover and stego images.
6. Run the classifier to determine detectability for each image size.
7. ...? CLARIFY

- We'll choose $r_1, ..., r_4$ such that the "middle" image size is in the "middle" among image sizes in terms of detectability. CLARIFY
- Something about number of non-zero coefficients...

2.11 07/11/18

- What I did:
  - Created the file structure on the server.
    - Each `actor00003/sizeXXXX/` directory has one subdirectory called `cover`.
    - We need to decide/calculate how many bits of payload to embed for each size before creating subdirectories for all the different payload sizes.
  - Changed `initial_curation.py` so that constants in the file are instead passed in as command-line arguments.
    - Reran it and it was almost twice as fast (11 vs 19 minutes), though the speedup is probably not related to this change.
  - Finished `compute_probabilities.py`. It finds a λ such that:

    $\sum_{i=1}^{N} H_2(\pi_i) \in [m, m+1)$, where m is the payload size to simulate
  - Wrote `crop.py` and ran it for the other nine image sizes.
    - It crops 8×8 blocks evenly from the top/bottom and right/left.
    - The process is documented in Section 1.1.3.
  - Refactored the J-UNIWARD code (C++ source files) for readability and uploaded them to my GitHub repository in the `j-uniward` directory.
    - Created a version that integrates Dr. Ker's hack to save the costs to a file (in ASCII) without doing the actual embedding.
    - 99% sure the costs are output in row order, which would be the intuitive way to implement it.
  - Started working on `compute_costs.py`, which runs the hacked J-UNIWARD on all images in a directory.

- Computing the costs for all the images of all sizes
  - On one core, it will take:

    $$50s \times 10000 \times (1 + 0.9 + ... + 0.1) \approx 763 \text{ hours} \approx 32 \text{ days}$$

  - I can use 8-10 of the server's 40 cores.
  - I'll run the script using `nohup` once per directory and obviously the process will finish faster for the smaller images, so I can start on the next task (feature computation) with those that finish first.
- Once the costs are computed, the next task is computing the features using JRM.
- Then, I'll start by using J-UNIWARD with 0.4 bits per non-zero coefficient. I then need to compute the features of the stego objects. Once this is done, I can train the classifier with the features of all the cover and stego objects.
  - The original plan was to use the ensemble classifier.
  - We will instead use a low-complexity linear classifier, which achieves similar performance but has a lower computational complexity.
- When training the classifier, it's important to keep the cover/stego objects pairs together (i.e. not put the cover in the training set and the stego in the testing test for cross-validation).
  - This is important because it ensures the classfier learns the correct boundary.
- The binary embedding I'll write will take the number of bits to embed as input.
  - We will compute the specific number of bits to run the embedding with by manually computing $r \cdot \sqrt{n}$ and $r \cdot \sqrt{n} \cdot \log n$, where n is the total number of pixels in each image and r is some constant we'll pick.
  - We'll pick r such that it makes the detectability of the "middle" image size the median among the detectabilities of all the sizes, where "detectability" refers to the classifier's accuracy.
- When the classifier training function asks for the costs "row-by-row", they mean it should be a big matrix where the first half of the rows are the costs of the cover images, in order, and the second half are the costs of the stego images, in the same order.

2.12 31/10/18

- What I did:
  - Put together this document
  - Organized all documents and scripts in my (private) GitHub repository
  - Fixed `initial_curation.py` (the problem is documented in Section 3.2) and I successfully ran it on the server
    - Original images: `/array/vlasov/actor00003/original`
    - All 3072×2304, grayscale, landscape images are in a new directory `/array/vlasov/actor00003/size3072`
  - Learned how to use `pyplot`, plotted H_2 as an exercise
  - Computed the image sizes we'll use (the process and results are described in Section 1.1.2)
    - The method discussed on 24/10/18 doesn't work. It does produce equally sized intervals (in terms of the difference in the total number of pixels between consecutive sizes), but only between 320×240 and the ninth-largest size since this interval is only around $70,000$. The ninth-largest size would be 960×720, which is clearly much smaller than 3072×2304.
    - In order to get sizes linearly distributed in terms of the total number of pixels, the interval needs to be closer to $700,000$ pixels.
  - Started working on `compute_probabilities.py`
- *Is the value of λ bounded? How should the binary search (in the context of PLS) work?*
  - $\lambda = 0$ corresponds to maximum entropy (aka. maximum payload) because then $\pi_i = \frac{1}{1+e^{\lambda c_i}} = \frac{1}{2}$
  - As $\lambda \to \infty$, $\pi_i \to 0$
  - The order of magnitude of λ depends on the order of magnitude of the costs.
  - The binary search will have two stages:
    1. Exponential search to find an upper bound on λ. This will involve trying exponentially large values such as $0, 1, 10, 100, ...$ until a value is found such that $\sum_{i=1}^{N} H_2(\pi_i) < M$
    2. Suppose the first value where this inequality holds is $\lambda = 10^n$. We now do a binary search for λ with a lower bound of 10^{n-1} and an upper bound of 10^n and we want to find a value

such that $\sum_{i=1}^{N} H_2(\pi_i) \in [m, m+1)$, where m is the number of payload bits.

- In Dr. Ker's paper "On the Relationship Between Embedding Costs and Steganographic Capacity" from June 2018, he writes about how if the detector knows the costs $c_1, c_2, ...c_N$, then the objective that should be minimized is $\sum_{i=1}^{N} c_i \pi_i^2$, which is the same as the objective in PLS except with the π_i terms squared.
  - This is a possible project extension.
  - The tricky part is computing the probabilities since the optimal solution is no longer $\pi_i = \frac{1}{1+e^{\lambda c_i}}$. Instead, it's $\frac{\pi_i}{H_2'(\pi_i)} = \lambda c_i$.
  - The probabilities can be computed by running Newton-Raphson several times (Dr. Ker did it 8 times)
  - I don't need to tackle this now, but it's worth keeping in mind.
- When I use Dr. Ker's J-UNIWARD hack, I need to make sure that I work out the order in which the costs are written to the file.
  - It's hard to tell just by looking at the costs whether or not they're in the right order. If I'm wrong, I'll probably find out since the embedding will be very detectable.
  - It's very likely that the 8×8 blocks are analyzed from left to right, top to bottom. However, within each block the costs could be left to right, top to bottom **or** in the zigzag order used to store the quantized coefficients. I need to check this.
- Once I compute the probabilities, it might be a good idea to use Python's `random.seed(..)` method (with the image number as the seed) in order to do the embedding. It can be used to determine whether or not to change each coefficient and so I'll always get the same embedding with the same cover, modulo rounding.
- Dr. Ker has a faster version of JRM for feature extraction.
- Tips:
  - After embedding, open the stego image to make sure nothing got messed up (e.g. due to the order of the costs or coefficients).
  - It would be a good idea to write some scripts to check things like:
    - The number of coefficients that differ between the cover and stego images is $\approx \sum_{i=1}^{N} \pi_i$

    - Coefficients that differ between the cover and stego images only differ by ± 1
  - Test things out on small images (e.g. 64×64) to save time in case there are bugs.

2.13 24/10/18

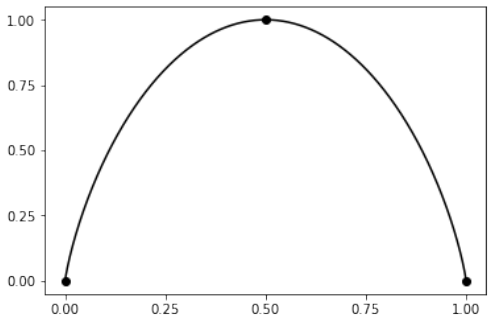
- What I did:
  - Read Chapter 3 of the Advanced Security notes on steganography
  - Wrote a script (`initial_curation.py`) to find all the largest images in the `actor00003` directory and then make them all grayscale and landscape (described in Section 1.1.1)
    - Wasn't quite working due to "`Empty input file`" error when performing multiple `jpegtran` operations
- Action plan:
  1. Calculate image sizes
     - Preserve the 4:3 aspect ratio, not because we have to but because we can and it means we can keep things as similar as possible
     - The largest image size we'll use is 3072×2304 since that's the size of the largest `actor00003` images.
     - The smallest size will be 320×240 since that's a relatively common image size (and it has a 4:3 aspect ratio)
     - The short-edge dimensions will be computed by hand by calculating $240x$ (where $x = \sqrt{1}, \sqrt{2}, ..., \sqrt{10}$) and then rounding to the nearest multiple of 24. Then the long-edge dimensions are calculated such that the 4:3 ratio is maintained.
  2. Create the directory structure on the server in `/array/vlasov/`
     - Keep a copy of all the original images in `actor00003/original`
     - Create one directory per image size, called `size3072` (for instance)
     - For each size, create two subdirectories:
       (a) One for the unaltered images, called `cover`
       (b) One per number of payload bits, called `stego-1234bits`
     - Each `cover` subdirectory will have three files per cover image:
       (a) `image12345.jpg`: the unaltered image
       (b) `image12345.costs`: the costs computed by J-UNIWARD
       (c) `image12345.fea`: the features computed by JRM

- Each `stego-1234bits` subdirectory will have one file per stego image:
  (a) `image12345.jpg`: the stego image, which is the cover image `sizeXXXX/cover/image12345.jpg` with a 1234-bit message embedded in it

3. Crop the 3072×2304 cover images to the sizes calculated in task 1. Do this by cropping 8×8 pixel blocks evenly from the top/bottom and right/left.
4. Generate the costs (using Dr. Ker's slighty modified J-UNIWARD code) and features (using JRM) for all the cover images of all the different sizes.
   - JRM produces 22510 real numbers (the features)
   - Up to me how to store them, but ASCII is probably the most portable
5. Use J-UNIWARD to embed 0.4 bits per non-zero AC coefficient in some of the covers.
6. Write a function that takes the number of payload bits as input and computes the probabilities with which each coefficient changes during (binary) embedding.
   - Goal: given the costs $c_1, c_2, ...c_N$ (where N is the total number of coefficients) of changing each coefficient (by adding or subtracting one), compute the probabilities $\pi_1, \pi_2, ..., \pi_N$ of making each of these changes
   - Size of the payload: $\sum_{i=1}^{N} H_2(\pi_i)$
     * H_2 is the "entropy" and is defined as:

$$H_2(x) = -x \cdot \log_2 x - (1-x) \cdot \log_2(1-x)$$

     * Graph of H_2:



   - Average total cost: $\sum_{i=1}^{N} c_i \pi_i$

- Two (equivalent) optimization problems for computing the payload size:
  (a) Distortion-limited sender (DLS)

$$\text{Maximize } \sum_{i=1}^{N} H_2(\pi_i) \text{ such that } \sum_{i=1}^{N} c_i \pi_i \leq C$$

  (b) Payload-limited sender (PLS)

$$\text{Minimize } \sum_{i=1}^{N} c_i \pi_i \text{ such that } \sum_{i=1}^{N} H_2(\pi_i) \geq M$$

- For some fixed λ, we can compute the probabilities:

$$\pi_i = \frac{1}{1 + e^{\lambda c_i}}$$

- We'll use PLS, where M is the payload size.
  * The optimal solution is when $\sum_{i=1}^{N} H_2(\pi_i) = M$
  * $\sum_{i=1}^{N} H_2(\pi_i)$ is actually monotonically decreasing, so we can find a value of λ such that $\sum_{i=1}^{N} H_2(\pi_i) = M$ for any M we choose. Then, we can compute the probabilities $\pi_1, \pi_2, ..., \pi_N$ using this value of λ.
  * The end goal is to do the embedding ourselves by modifying each coefficient with these probabilities.

- *Is 80 a standard JPEG quality factor (QF)?* In the massive image database released by Flickr, the most common QFs were 100, the QF used by iPhones, and 80. So, we're using 80 because that gives us a greater selection of images.

2.14 17/10/18

- What I did:
  - Read Chapters 1 and 2 of the Advanced Security notes on steganography
  - Read the 2008 paper "The Square Root Law of Steganographic Capacity"

- Discussed questions I had about Chapter 1 (Steganography) and Chapter 2 (Steganalysis) of the Advanced Security notes and about the 2008 paper.

  - *What is downsampling?* Shrinking
  - *When you take a pictures on your phone, what happens?* Captures raw image, immediately compresses it as a JPEG, and discards the raw image
  - *What determines a cover's "source"?* Primarily the camera. The camera's ISO setting, in particular, is very important. The subject of the photos don't make much of a difference.
  - *In JPEG compression, don't you lose some information when dividing the image into* 8×8 *pixel blocks?* No, the DCT is linear (i.e. 1-to-1 mapping from 8×8 blocks to coefficients)
  - *Is a JPEG decompressed every time you view it on a computer?* Yes
  - *When LSBR is used on RGB images, which bit(s) are changed?* Good question - it depends, but usually the LSBs of all three components (in sync)
- After embedding a payload, the original cover is destroyed. Otherwise, two nearly identical images would be floating around and Alice could easily be outed if someone got their hands on both versions.

2.15 03/10/18

- What I did: N/A
- Discussed software to be used for embedding (J-UNIWARD), feature extraction (JRM), and detection (ensemble of linear classifiers)
  - All the software is here
- Server's IP: 163.1.88.150
- Amounts of payload to embed: $O(1)$, $O(\sqrt{n})$, $O(\sqrt{n}\log n)$, $O(n)$
- $m \sim \frac{\sqrt{DC}}{2} \log \frac{C}{D}$
- TIME EVERYTHING
- I will test new embedding and new detecting methods and I could also try old embedding and new detecting methods
- Total amount of space needed (assuming around 10,000 images are used):
  - Images: $2MB \times 10000 \times 9 \approx 180GB$
  - Costs: $8B \times 5M \times 10000 \approx 400GB$
  - Features: $170KB \times 10000 \times 9 \approx 17GB$

Chapter 3

Notes to Self

3.1 Useful Commands

- Run a command in the background so that you can keep using the terminal or close it
  - `nohup python script.py &> script_output.out &`
- Check on processes that are running
  - `ps aux | grep vlasov`
- See what processes are currently running, how many resources they're using, etc.
  - `htop`
- View information on how much RAM is used, available, etc.
  - `free`
- Compile MATLAB code
  - `mcc -m [-v] abc_xyz.m`
- Run script generated by `mcc`
  - `./run_abc_xyz.sh /usr/local/matlab-r2014a/`

3.2 Lessons Learned

- The input and output file to `jpegtran` can't be the same, otherwise you get an "`Empty input file`" error.
- If it looks like directories on the server have disappeared, turn off f.lux or change the colour settings in `.bashrc`.

- Beware that in Python versions earlier than 2.3, the `log` function computes the natural logarithm. In version 2.3, an optional `base` argument was added in order to specify the base of the logarithm. So, if you execute `log(64,2)` with a Python version earlier than 2.3, the second argument is ignored and you get the natural logarithm of 64.
- If I use `at` to schedule tasks, I will not have access to the standard output because it tries to email it to me, which fails because there is no mail transfer agent installed.
- Back up features (`.mat` files) to `/home` because it is backed up whereas `/array` is not. Nothing happened yet, but just in case. Last backup was 27/02/19.

Chapter 4

Actor3 Experiment Results

4.1 Cover Images

4.1.1 Initial Curation

- 30/10/18: `initial_curation.py` (before I changed constants to command-line arguments)
  - $1131.18478608s \approx 18m51s$
- 01/11/18: `initial_curation.py --from-dir original/ --to-dir size3072/cover/`
  - $655.185225964s \approx 10m55s$

4.1.2 Cropping

- 01/11/18: `crop.py --from-dir size3072/cover --to-dir sizeW/cover/ --width W --height H`, where:

W	H	Seconds	Approx. Time
2912	2184	689.414359808	11m29s
2720	2040	662.552460909	11m02s
2528	1896	662.54279089	11m02s
2304	1728	632.872202158	10m32s
2048	1536	605.926501989	10m05s
1792	1344	555.097690105	9m15s
1472	1104	511.460752964	8m31s
1056	792	438.49830699	7m18s
320	240	359.436480045	5m59s

4.1.3 Costs

- 10/11/18: `./J-UNIWARD-COSTS -v -I sizeX/cover/ -O sizeX/cover/ -a 0.4`

Width	Height	Seconds	Approx. Time
3072	2304	??	??
2912	2184	??	??
2720	2040	??	??
2528	1896	??	??
2304	1728	??	??
2048	1536	??	??
1792	1344	??	??
1472	1104	??	??
1056	792	??	??
320	240	6430.11	1h47m

  - For some unknown reason, the command for 320×240 is the only one that finished properly, in the sense that it computed the costs for all ~ 9500 images. The commands for the other nine image sizes either stopped mid-execution after computing the costs for a few hundred images, or continued running without making any progress (which is the case for 2912×2184 and 2720×2040, which ran for over 70 hours but stopped making progress).

- 17/11/18: `compute_costs.py -I sizeX/cover/ -O sizeX/cover/`

Width	Height	Seconds	Approx. Time
3072	2304	202775.362686	2d 8h 19m
2912	2184	194673.499774	2d 6h 4m
2720	2040	183598.260891	2d 2h 59m
2528	1896	172031.831308	1d 23h 47m
2304	1728	152188.728338	1d 18h 16m
2048	1536	129785.996801	1d 12h 3m
1792	1344	104988.846009	1d 5h 9m
1472	1104	74601.1954741	10h 43m
1056	792	39340.753726	10h 55m
320	240	3767.95246005	1h 2m

4.1.4 Features

- 10/11/18: `compute_features.py -I sizeX/cover/`

Width	Height	Seconds	Approx. Time
3072	2304	72,282.4331231	20h4m
2912	2184	63,869.6948001	17h44m
2720	2040	54,000.526902	15h0m
2528	1896	40,194.252851	11h9m
2304	1728	32,157.8610289	8h55m
2048	1536	30,295.748122	8h24m
1792	1344	18,653.2866731	5h10m
1472	1104	14,390.2565191	3h59m
1056	792	8,721.86998391	2h25m
320	240	6,430.11	1h22m

  - On 15/11/18, I checked the sums of the features to ensure that they all add up to the same constant. This constant turns out to be 1346 for each image's features, regardless of size.
  - However, it turns out that several hundred images' features were not computed.

- 17/11/18: `compute_features.py -I sizeX/cover/`
  - Unfortunately the timing information wasn't logged, but as a general idea, all processes finished after around 18-20 hours.

4.1.5 Feature Matrix

- First step (02/12/18): `combine_feature_files.py -I sizeX/cover/ -O features/sizeX_cover.fea`
  - No timing information was saved for any of the sizes.
- Second step (02/12/18): `./run_txt_to_mat.sh /usr/local/matlab-r2014a/ features/sizeX_cover.fea features/sizeX_cover.mat`
  - My `txt_to_mat.m` script doesn't produce timing information.

4.2 Ternary Embedding (with $\alpha = 0.1$)

4.2.1 Embedding

- `./J-UNIWARD-EMBED-WITH-COSTS -v -I sizeX/cover -O sizeX/stego-juni-01 -a 0.1`

Width	Height	Seconds	Approx. Time	Date Finished
2304	1728	??	??	??
2048	1536	??	??	??
1792	1344	??	??	??
1472	1104	316072	3d15h	02/11/18
1056	792	35545	9h52m	29/11/18
320	240	3192.98	53m	29/11/18

- Sizes $1792 \times 1344, 2048 \times 1536, 2304 \times 1728$ didn't terminate properly when they were first run. The processes ran for over ten days and were making progress but would randomly stall at various times, sometimes for 30 minutes, sometimes for 6 hours. So, the processes were killed, the script was adapted so that it would only embed in the cover images that did not already have corresponding stego images, and it was rerun for those three sizes.
- Since the first run stalled multiple times and had to be terminated prematurely, there is no timing information for these three sizes.
- The $J_{0.1}$ stego images have now been generated for all six sizes.

4.2.2 Features

- `compute_features.py -I sizeX/stego-juni-01/`

Width	Height	Seconds	Approx. Time	Date
2304	1728	13062.3725212	3h37m	13/12/18
2048	1536	12428.002079	3h27m	13/12/18
1792	1344	8581.41911697	2h23m	12/12/18
1472	1104	8461.04521799	2h21m	02/12/18
1056	792	5645.03076911	1h34m	02/12/18
320	240	735.175777912	12m	29/11/18

- Only the six smallest image sizes were used.

4.2.3 Feature Matrix

- First step: `combine_feature_files.py -I sizeX/stego-juni-01/ -O features/sizeX_juni_01.fea`

Width	Height	Seconds	Approx. Time	Date
2304	1728	39.6396141052	39s	13/12/18
2048	1536	40.74949193	40s	13/12/18
1792	1344	80.3196239471	1m20s	13/12/18
1472	1104	199.391219139	3m19s	12/12/18
1056	792	199.67672205	3m19s	02/12/18
320	240	??	??	??

– Timing information for 320×240 is missing.

- Second step: `./run_txt_to_mat.sh /usr/local/matlab-r2014a/ features/sizeX_juni_01.fea features/sizeX_juni_01.mat`

  – My `txt_to_mat.m` script doesn't produce timing information.

4.2.4 Linear Classifier

- `./run_juniward_test.sh /usr/local/matlab-r2014a/ features/sizeX_cover.mat features/sizeX_juni_0X.mat`

Width	Height	MinPE	Seconds	Approx. Time	Date
2304	1728	0.3743	436.3494	7m	13/12/18
2048	1536	0.3809	491.4821	8m	13/12/18
1792	1344	0.3981	375.6563	6m	13/12/18
1472	1104	0.4208	413.5771	6m	12/12/18
1056	792	0.4386	829.9007	13m	10/12/18
320	240	0.4780	994.2325	16m	02/12/18

4.3 Ternary Embedding (with other α values)

- Since none of the MinPE values in Section 4.2.4 were quite low enough, I ran the embedding again on a subset of the sizes with some other values of α.

- `./J-UNIWARD-EMBED-WITH-COSTS -v -I sizeX/cover -O sizeX/stego-juni-01 -a alpha`, where `alpha` is:

Width	Height	α	Seconds	Approx. Time	Date Finished
1056	792	0.3	?	?	04/01/19
1056	792	0.4	31621.6	8h47m	14/12/18
320	240	0.3	3316.72	55m	14/12/18
320	240	0.4	3307.1	55m	14/12/18
320	240	0.5	3305.58	55m	14/12/18
320	240	0.6	?	?	03/01/19

  – Timing information for 320×240 ($\alpha = 0.6$) and 1056×792 ($\alpha = 0.3$) is missing.

4.3.1 Features

- `compute_features.py -I sizeX/stego-juni-0X/`

Width	Height	α	Seconds	Approx. Time	Date Finished
1056	792	0.3	7923.50714922	2h12m	04/01/19
1056	792	0.4	3425.78458905.6	57m	14/12/18
320	240	0.3	1459.43398404	24m	14/12/18
320	240	0.4	1461.83910203	24m	14/12/18
320	240	0.5	1459.43398404	24m	14/12/18
320	240	0.6	2298.33446884	24m	04/01/19

4.3.2 Feature Matrix

- First step: `combine_feature_files.py -I sizeX/stego-juni-0X/ -O features/sizeX_juni_0X.fea`

Width	Height	α	Seconds	Approx. Time	Date Finished
1056	792	0.3	55.0291929245	55s	08/01/19
1056	792	0.4	49.0757801533	49s	14/12/18
320	240	0.3	266.531414986	4m	14/12/18
320	240	0.4	295.562961817	4m	14/12/18
320	240	0.5	289.210170031	4m	14/12/18
320	240	0.6	113.729305029	1m	04/01/19

- Second step: `./run_txt_to_mat.sh /usr/local/matlab-r2014a/ features/sizeX_juni_0X.fea features/sizeX_juni_0X.mat`
  - My `txt_to_mat.m` script doesn't produce timing information.

4.3.3 Linear Classifier

- `./run_juniward_test.sh /usr/local/matlab-r2014a/ features/sizeX_cover.mat features/sizeX_juni_0X.mat`

Width	Height	α	MinPE	Seconds	Approx. Time	Date Finished
1056	792	0.3	0.2249	926.3549	15m	08/01/19
1056	792	0.4	0.1297	572.7521	9m	15/12/18
320	240	0.3	0.3997	1075.703	17m	15/12/18
320	240	0.4	0.3500	1047.573	17m	15/12/18
320	240	0.5	0.2791	1127.515	18m	15/12/18

4.4 Binary Embedding

4.4.1 Embedding

- Command:
  `./BINARY-EMBED -v -I sizeX/cover -O sizeX/stego-Yb -b Y`
- Embedding with $O(1)$ bits:

Width	Height	Bits	Seconds	Approx. Time	Date Finished
3072	2304	49176	??	??	16/03/19
3072	2304	70252	>61000	>16h56m	17/02/19
3072	2304	91327	??	??	28/03/19
2912	2184	49176	??	??	27/03/19
2912	2184	70252	>108000	>1d6h	17/02/19
2912	2184	91327	??	??	28/03/19
2720	2040	49176	127453.5	1d11h	23/03/19
2720	2040	70252	>80000	>22h13m	17/02/19
2720	2040	91327	140831.4	1d15h	22/03/19
2528	1896	49176	111813.3	1d7h	20/03/19
2528	1896	70252	>101612	>1d4h	17/02/19
2528	1896	91327	116834.6	1d8h	22/03/19
2304	1728	49176	95216.4	1d2h	19/03/19
2304	1728	70252	>98000	>1d3h	11/02/19
2304	1728	91327	99607.8	1d3h	19/03/19
2048	1536	49176	81248.75	22h34m	07/03/19
2048	1536	70252	>4514.07	>1h15m	10/02/19
2048	1536	91327	83998.13	23h19m	07/03/19
1792	1344	49176	59433.77	16h30m	05/03/19
1792	1344	70252	62200	17h16m	11/02/19
1792	1344	91327	54603.88	15h10m	15/03/19
1472	1104	49176	39487.84	10h58m	05/03/19
1472	1104	70252	42994.4	11h56m	04/02/19
1472	1104	91327	44439.1	12h20m	05/03/19
1056	792	49176	24320.21	6h45m	04/03/19
1056	792	70252	20011.3	5h33m	03/02/19
1056	792	91327	19933.62	5h32m	04/03/19
320	240	49176	2374.767	39m	03/03/19
320	240	70252	2700.35	45m	03/02/19
320	240	N/A	N/A	N/A	N/A

- Embedding with $O(\sqrt{n})$ bits:

Width	Height	Bits	Seconds	Approx. Time	Date Finished
3072	2304	73764	225602.2	2d14h	03/03/19
3072	2304	105378	>51000	>14h	17/02/19
3072	2304	136991	??	??	20/03/19
2912	2184	69922	??	??	04/03/19
2912	2184	99889	–	–	10/02/19
2912	2184	129856	??	??	22/03/19
2720	2040	65312	126430.1	1d11h	05/03/19
2720	2040	93303	–	–	17/02/19
2720	2040	121294	149336.1	1d17h	22/03/19
2528	1896	60702	118372.8	1d8h	06/03/19
2528	1896	86717	–	–	10/02/19
2528	1896	112732	115862.0	1d8h	16/03/19
2304	1728	55323	87654.63	1d0h	07/03/19
2304	1728	79033	–	–	10/02/19
2304	1728	102743	104371	1d4h	15/03/19
2048	1536	49176	81248.75	22h34m	07/03/19
2048	1536	70252	>4514.07	>1h15m	10/02/19
2048	1536	91327	83998.13	23h19m	07/03/19
1792	1344	43029	62264.96	17h17m	05/03/19
1792	1344	61470	–	–	10/02/19
1792	1344	79911	70561.84	22h11m	06/03/19
1472	1104	35345	38142.99	10h35m	03/03/19
1472	1104	50493	45099.3	12h31m	04/02/19
1472	1104	65641	36643.5	10h10m	06/03/19
1056	792	25356	17914.98	4h58m	03/03/19
1056	792	36223	>683.576	>11m	10/02/19
1056	792	47090	18208.44	5h3m	16/03/19
320	240	7683	1913.174	31m	02/03/19
320	240	10976	1685.92	28m	03/02/19
320	240	14269	2034.716	33m	03/03/19

- Embedding with $O(\log n \cdot \sqrt{n})$ bits:

Width	Height	Bits	Seconds	Approx. Time	Date Finished
3072	2304	77762	??	??	03/03/19
3072	2304	111089	>43000	>11h56m	17/02/19
3072	2304	144416	??	??	25/03/19
2912	2184	73212	??	??	05/03/19
2912	2184	104589	>103355	>1d4h	23/02/19
2912	2184	135966	182316.1	2d2h	26/03/19
2720	2040	67790	137358.0	1d14h	06/03/19
2720	2040	96843	>112994	>1d7h	23/02/19
2720	2040	125895	166740.0	1d22h	25/03/19
2528	1896	62410	??	??	06/03/19
2528	1896	89158	103358.15	1d4h	24/02/19
2528	1896	115905	119591.7		17/03/19
2304	1728	56194	82540.6	22h55m	29/03/19
2304	1728	80278	89343	1d	24/02/19
2304	1728	104361	95074.47	1d2h	15/03/19
2048	1536	49176	81248.75	22h34m	07/03/19
2048	1536	70252	>4514.07	>1h15m	10/02/19
2048	1536	91327	83998.13	23h19m	07/03/19
1792	1344	42261	62248.53	17h17m	05/03/19
1792	1344	60373	59000	16h23m	17/02/19
1792	1344	78485	55638.11	15h27m	06/03/19
1472	1104	33785	38831.33	10h47m	03/03/19
1472	1104	48264	45000	12h30m	17/02/19
1472	1104	62744	44507.47	12h21m	05/03/19
1056	792	23111	15977.93	4h26m	03/03/19
1056	792	33016	–	–	16/02/19
1056	792	42921	20978.56	5h49m	04/03/19
320	240	5777	1825.240	30m	03/03/19
320	240	8253	>635.221	>10m	10/02/19
320	240	10728	1933.976	32m	03/03/19

- Embedding with $O(n)$ bits:

Width	Height	Bits	Seconds	Approx. Time	Date Finished
3072	2304	110647	172496.9	1h23h	18/03/19
3072	2304	158067	216142.3	2d12h	24/02/19
3072	2304	205487	160215.2	1d20h	29/03/19
2912	2184	99421	??	??	25/03/19
2912	2184	142030	–	2d5h	25/02/19
2912	2184	184640	144727.7	1d16h	29/03/19
2720	2040	86743	143952.2	1d15h	23/03/19
2720	2040	123919	141025.7	1d15h	26/02/19
2720	2040	161094	157220.7	1d19h	26/03/19
2528	1896	74929	??	??	07/03/19
2528	1896	107042	113238.8	1d7h	27/02/19
2528	1896	139154	??	??	18/03/19
2304	1728	62239	97526.05	1d3h	16/03/19
2304	1728	88912	97086.76	1d2h	26/02/19
2304	1728	115586	99207.54	1d3h	17/03/19
2048	1536	49176	81248.75	22h34m	07/03/19
2048	1536	70252	>4514.07	>1h15m	10/02/19
2048	1536	91327	83998.13	23h19m	07/03/19
1792	1344	37650	63098.06	17h31m	06/03/19
1792	1344	53786	55234.16	15h20m	25/02/19
1792	1344	69922	66453.09	18h27m	07/03/19
1472	1104	25404	34509.6	9h35m	04/03/19
1472	1104	36292	38449	10h40m	25/02/19
1472	1104	47180	45211.98	12h33m	05/03/19
1056	792	13074	21918.58	6h5m	04/03/19
1056	792	18677	15100	4h11m	16/02/19
1056	792	24281	16819.14	4h40m	04/03/19
320	240	1200	1498.869	24m	02/03/19
320	240	1715	1382.08	23m	03/02/19
320	240	2229	1657.451	27m	03/03/19

4.4.2 Features

- Command: `compute_features.py -I sizeX/stego-Yb`
- Features with $O(1)$ bits:

Width	Height	Bits	Seconds	Approx. Time	Date Finished
3072	2304	49176	87468.4551961	1d0h	16/03/19
3072	2304	70252	46984.4500248	13h3m	18/02/19
3072	2304	91327	28654.6217229	7h57m	28/03/19
2912	2184	49176	22817.8052733	6h20m	27/03/19
2912	2184	70252	37558.0894871	10h25m	17/02/19
2912	2184	91327	26109.3570216	7h15m	28/03/19
2720	2040	49176	42703.7677369	11h51m	23/03/19
2720	2040	70252	36072.916594	10h1m	17/02/19
2720	2040	91327	65526.0531928	18h12m	22/03/19
2528	1896	49176	130436.69898	1d12h	20/03/19
2528	1896	70252	35909.306066	9h58m	17/02/19
2528	1896	91327	24085.4321764	6h41m	22/03/19
2304	1728	49176	47811.7135792	13h16m	19/03/19
2304	1728	70252	35419.6147239	9h50m	17/02/19
2304	1728	91327	54276.669075	15h4m	20/03/19
2048	1536	49176	29402.2739372	8h10m	07/03/19
2048	1536	70252	33207.936137	9h13m	17/02/19
2048	1536	91327	36380.2966471	10h6m	07/03/19
1792	1344	49176	??	??	05/03/19
1792	1344	70252	26210.7519009	7h16m	17/02/19
1792	1344	91327	10081.4698121	2h48m	16/03/19
1472	1104	49176	8794.41904068	2h26m	05/03/19
1472	1104	70252	17386.2786419	4h49m	16/02/19
1472	1104	91327	16430.9569552	4h33m	05/03/19
1056	792	49176	4519.55386352	1h15m	04/03/19
1056	792	70252	29033.266953	8h3m	04/02/19
1056	792	91327	15869.6408393	4h24m	04/03/19
320	240	49176	7610.020973205	2h6m	03/03/19
320	240	70252	813.488664865	13m	03/02/19
320	240	N/A	N/A	N/A	N/A

- Features with $O(\sqrt{n})$ bits:

Width	Height	Bits	Seconds	Approx. Time	Date Finished
3072	2304	73764	80922.0440509	22h28m	03/03/19
3072	2304	105378	49255.76351	13h40m	17/02/19
3072	2304	136991	61661.2307301	17h7m	21/03/19
2912	2184	69922	85130.7830179	23h38m	04/03/19
2912	2184	99889	42486.8198349	11h48m	17/02/19
2912	2184	129856	29296.6336634	8h8m	22/03/19
2720	2040	65312	84578.9741294	23h29m	05/03/19
2720	2040	93303	36314.8657269	10h5m	17/02/19
2720	2040	121294	26779.7132091	7h26m	22/03/19
2528	1896	60702	85851.781539	23h50m	06/03/19
2528	1896	86717	38099.1221862	10h34m	17/02/19
2528	1896	112732	47043.5258255	13h4m	16/03/19
2304	1728	55323	25570.4075403	7h6m	07/03/19
2304	1728	79033	35428.6774151	9h50m	17/02/19
2304	1728	102743	16549.4431532	4h35m	15/03/19
2048	1536	49176	29402.2739372	8h10m	07/03/19
2048	1536	70252	33207.936137	9h13m	17/02/19
2048	1536	91327	36380.2966471	10h6m	07/03/19
1792	1344	43029	29298.2088437	8h8m	05/03/19
1792	1344	61470	24724.9334159	6h52m	16/02/19
1792	1344	79911	20589.7238495	5h43m	06/03/19
1472	1104	35345	35528.2139196	9h52m	03/03/19
1472	1104	50493	16583.3313291	4h36m	16/02/19
1472	1104	65641	27124.7286665	7h32m	06/03/19
1056	792	25356	7695.59258175	2h8m	03/03/19
1056	792	36223	4043.80457211	1h7m	10/02/19
1056	792	47090	10989.9993079	3h3m	16/03/19
320	240	7683	13420.048642159	3h43m	03/03/19
320	240	10976	8814.44127607	2h26m	03/02/19
320	240	14269	9699.32517433	2h41m	03/03/19

- Features with $O(\log n \cdot \sqrt{n})$ bits:

Width	Height	Bits	Seconds	Approx. Time	Date Finished
3072	2304	77762	64165.0254614	17h49m	03/03/19
3072	2304	111089	15667.311007	9h54m	18/02/19
3072	2304	144416	66243.4391727	18h24m	25/03/19
2912	2184	73212	98611.1762438	1d3h	05/03/19
2912	2184	104589	19566.717365	5h26m	23/02/19
2912	2184	135966	63498.5347029	17h38m	26/03/19
2720	2040	67790	81036.1087067	22h30m	06/03/19
2720	2040	96843	18377.3187139	5h6m	23/02/19
2720	2040	125895	59562.0961859	16h32m	25/03/19
2528	1896	62410	32776.2211308	9h6m	06/03/19
2528	1896	89158	36394.246537	10h6m	25/02/19
2528	1896	115905	46082.104017	12h48m	18/03/19
2304	1728	56194	14146.2479212	3h55m	29/03/19
2304	1728	80278	26904.6615889	7h28m	24/02/19
2304	1728	104361	14877.2953498	4h7m	16/03/19
2048	1536	49176	29402.2739372	8h10m	07/03/19
2048	1536	70252	33207.936137	9h13m	17/02/19
2048	1536	91327	36380.2966471	10h6m	07/03/19
1792	1344	42261	30188.3648422	8h23m	05/03/19
1792	1344	60373	21166.0959091	5h52m	18/02/19
1792	1344	78485	25893.1390047	7h11m	06/03/19
1472	1104	33785	14645.4112713	4h4m	03/03/19
1472	1104	48264	20401.2422099	5h40m	17/02/19
1472	1104	62744	27497.6112786	7h38m	05/03/19
1056	792	23111	7018.70651841	1h56m	03/03/19
1056	792	33016	7414.97025299	2h3m	16/02/19
1056	792	42921	12899.8471687	3h34m	04/03/19
320	240	5777	7602.513247014	2h6m	03/03/19
320	240	8253	1713.00027585	28m	16/02/19
320	240	10728	9776.47659087	2h42m	03/03/19

- Features with $O(n)$ bits:

Width	Height	Bits	Seconds	Approx. Time	Date Finished
3072	2304	110647	76411.2817299	21h13m	18/03/19
3072	2304	158067	40486.1764619	11h14m	27/02/19
3072	2304	205487	77217.4703996	21h26m	29/03/19
2912	2184	99421	51850.9604163	14h24m	25/03/19
2912	2184	142030	26120.325207	7h15m	25/02/19
2912	2184	184640	21018.7189531	5h50m	29/03/19
2720	2040	86743	36584.3893359	10h9m	23/03/19
2720	2040	123919	26204.7609549	7h16m	27/02/19
2720	2040	161094	22522.3931799	6h15m	26/03/19
2528	1896	74929	91141.6428967	1d1h	15/03/19
2528	1896	107042	15718.79787564	4h21m	27/02/19
2528	1896	139154	33803.4779005	9h23m	18/03/19
2304	1728	62239	22441.9120758	6h14m	17/03/19
2304	1728	88912	42948.730552	11h55m	27/02/19
2304	1728	115586	14984.3578377	4h9m	17/03/19
2048	1536	49176	29402.2739372	8h10m	07/03/19
2048	1536	70252	33207.936137	9h13m	17/02/19
2048	1536	91327	36380.2966471	10h6m	07/03/19
1792	1344	37650	43932.3998611	12h12m	06/03/19
1792	1344	53786	15211.650321	4h13m	25/02/19
1792	1344	69922	15518.4198549	4h18m	07/03/19
1472	1104	25404	29844.1452055	8h17m	04/03/19
1472	1104	36292	11716.5168169	3h15m	25/02/19
1472	1104	47180	16724.4930618	4h38m	05/03/19
1056	792	13074	10193.1102669	2h49m	04/03/19
1056	792	18677	13655.626116	3h47m	17/02/19
1056	792	24281	15550.941546	4h19m	05/03/19
320	240	1200	13085.426150084	3h38m	03/03/19
320	240	1715	8862.28981304	2h27m	03/02/19
320	240	2229	9861.31005359	2h44m	03/03/19

4.4.3 Feature Matrix

- First step: `combine_feature_files.py -I sizeX/stego-Yb/ -O features/sizeX_binary_Yb.fea`
- Feature matrix with $O(1)$ bits:

Width	Height	Bits	Seconds	Approx. Time	Date Finished
3072	2304	49176	227.739675999	3m	21/03/19
3072	2304	70252	252.853466988	4m	26/02/19
3072	2304	91327	50.8630750179	0m	28/03/19
2912	2184	49176	124.856258154	2m	27/03/19
2912	2184	70252	85.6574821472	1m	17/02/19
2912	2184	91327	50.9590110779	0m	28/03/19
2720	2040	49176	210.355884075	3m	23/03/19
2720	2040	70252	38.9857468605	0m	17/02/19
2720	2040	91327	79.8529691696	1m	22/03/19
2528	1896	49176	38.2506098747	0m	21/03/19
2528	1896	70252	129.218651056	2m	17/02/19
2528	1896	91327	44.696778059	0m	22/03/19
2304	1728	49176	219.060958147	3m	19/03/19
2304	1728	70252	358.85760794	5m	17/02/19
2304	1728	91327	125.304362059	2m	20/03/19
2048	1536	49176	632.630553007	10m	07/03/19
2048	1536	70252	862.218221903	14m	17/02/19
2048	1536	91327	1228.48091912	20m	07/03/19
1792	1344	49176	319.734992981	5m	05/03/19
1792	1344	70252	390.150359869	6m	17/02/19
1792	1344	91327	96.4794027805	1m	16/03/19
1472	1104	49176	43.8332381248	0m	05/03/19
1472	1104	70252	1815.72977614	30m	17/02/19
1472	1104	91327	103.874501944	1m	05/03/19
1056	792	49176	43.5582931042	0m	04/03/19
1056	792	70252	133.089641094	2m	10/02/19
1056	792	91327	84.5707299709	1m	04/03/19
320	240	49176	61.6737239361	1m	03/03/19
320	240	70252	334.823001146	5m	03/02/19
320	240	N/A	N/A	N/A	N/A

- Feature matrix with $O(\sqrt{n})$ bits:

Width	Height	Bits	Seconds	Approx. Time	Date Finished
3072	2304	73764	263.632461071	4m	03/03/19
3072	2304	105378	119.561875105	1m	17/02/19
3072	2304	136991	137.048567057	2m	21/03/19
2912	2184	69922	174.518545866	2m	04/03/19
2912	2184	99889	795.025964022	13m	17/02/19
2912	2184	129856	41.4731681347	0m	22/03/19
2720	2040	65312	324.896591902	5m	05/03/19
2720	2040	93303	107.072767019	1m	17/02/19
2720	2040	121294	62.4946548939	1m	22/03/19
2528	1896	60702	256.547324896	4m	06/03/19
2528	1896	86717	873.271565914	14m	17/02/19
2528	1896	112732	173.554177999	2m	17/03/19
2304	1728	55323	229.104845047	3m	07/03/19
2304	1728	79033	915.09699297	15m	17/02/19
2304	1728	102743	39.430989027	0m	15/03/19
2048	1536	49176	632.630553007	10m	07/03/19
2048	1536	70252	862.218221903	14m	17/02/19
2048	1536	91327	1228.48091912	20m	07/03/19
1792	1344	43029	65.4516999722	1m	05/03/19
1792	1344	61470	1777.79198408	29m	17/02/19
1792	1344	79911	47.968957901	0m	06/03/19
1472	1104	35345	83.1389400959	1m	03/03/19
1472	1104	50493	1709.26175904	28m	16/02/19
1472	1104	65641	200.148355961	3m	06/03/19
1056	792	25356	195.849433184	3m	03/03/19
1056	792	36223	39.5040259361	0m	10/02/19
1056	792	47090	45.6129751205	0m	16/03/19
320	240	7683	172.7494128974	2m	03/03/19
320	240	10976	690.326555967	11m	04/02/19
320	240	14269	76.2257049084	1m	03/03/19

- Feature matrix with $O(\log n \cdot \sqrt{n})$ bits:

Width	Height	Bits	Seconds	Approx. Time	Date Finished
3072	2304	77762	343.621596098	5m	04/03/19
3072	2304	111089	113.954504967	1m	19/02/19
3072	2304	144416	140.097576857	2m	25/03/19
2912	2184	73212	363.530250072	6m	05/03/19
2912	2184	104589	36.0493149757	0m	24/02/19
2912	2184	135966	157.2450881	2m	26/03/19
2720	2040	67790	172.096813917	2m	06/03/19
2720	2040	96843	48.0687019825	0m	24/02/19
2720	2040	125895	157.019212961		25/03/19
2528	1896	62410	47.2514410019	0m	06/03/19
2528	1896	89158	106.045143843	1m	25/02/19
2528	1896	115905	184.936322927	3m	18/03/19
2304	1728	56194	46.648168087	0m	29/03/19
2304	1728	80278	106.953674006	1m	25/02/19
2304	1728	104361	110.258715868	1m	16/03/19
2048	1536	49176	632.630553007	10m	07/03/19
2048	1536	70252	862.218221903	14m	17/02/19
2048	1536	91327	1228.48091912	20m	07/03/19
1792	1344	42261	68.2365150452	1m	05/03/19
1792	1344	60373	107.047373056	1m	19/02/19
1792	1344	78485	48.856415987	0m	06/03/19
1472	1104	33785	194.523323059	3m	04/03/19
1472	1104	48264	970.601518869	16m	17/02/19
1472	1104	62744	77.1061918736	1m	05/03/19
1056	792	23111	176.880733013	2m	03/03/19
1056	792	33016	39.8880968094	0m	16/02/19
1056	792	42921	60.8147819042	1m	04/03/19
320	240	5777	47.0853788853	0m	03/03/19
320	240	8253	43.9101500511	0m	16/02/19
320	240	10728	62.5113809109	1m	03/03/19

- Feature matrix with $O(n)$ bits:

Width	Height	Bits	Seconds	Approx. Time	Date Finished
3072	2304	110647	126.241893053	2m	18/03/19
3072	2304	158067	73.3681468964	1m	27/02/19
3072	2304	205487	46.2296299934	0m	29/03/19
2912	2184	99421	70.4530329704	1m	25/03/19
2912	2184	142030	60.8014481068	1m	26/02/19
2912	2184	184640	41.1151740551	0m	29/03/19
2720	2040	86743	46.7586479187	0m	23/03/19
2720	2040	123919	50.7779140472	0m	27/02/19
2720	2040	161094	38.9449191093	0m	26/03/19
2528	1896	74929	197.348838806	3m	15/03/19
2528	1896	107042	38.95647192	0m	27/02/19
2528	1896	139154	44.4193429947	0m	18/03/19
2304	1728	62239	51.8338558674	0m	17/03/19
2304	1728	88912	97.6287519932	1m	27/02/19
2304	1728	115586	39.4433550835	0m	17/03/19
2048	1536	49176	632.630553007	10m	07/03/19
2048	1536	70252	862.218221903	14m	17/02/19
2048	1536	91327	1228.48091912	20m	07/03/19
1792	1344	37650	301.110005856	5m	06/03/19
1792	1344	53786	91.612528801	1m	26/02/19
1792	1344	69922	1041.00203395	17m	07/03/19
1472	1104	25404	84.4692189693	1m	04/03/19
1472	1104	36292	48.666615963	0m	25/02/19
1472	1104	47180	102.075462818	1m	05/03/19
1056	792	13074	40.3709020615	0m	04/03/19
1056	792	18677	296.103348017	4m	17/02/19
1056	792	24281	287.475348949	4m	05/03/19
320	240	1200	179.388769865	2m	03/03/19
320	240	1715	679.769860029	11m	04/02/19
320	240	2229	83.3646969795	1m	03/03/19

- Second step: `./run_txt_to_mat.sh /usr/local/matlab-r2014a/ features/sizeX_binary_Yb.fea features/sizeX_binary_Yb.mat`
  - My `txt_to_mat.m` script doesn't produce timing information.

4.4.4 Linear Classifier

- Command: `./run_juniward_test.sh /usr/local/matlab-r2014a/ features/sizeX_cover.mat features/sizeX_binary_Yb.mat`
- Classifier with $O(1)$ bits:

Width	Height	Bits	MinPE	Seconds	Approx. Time	Date Finished
3072	2304	49176	0.3828	494.0306	8m	21/03/19
3072	2304	70252	0.3099	467.0451	7m	26/02/19
3072	2304	91327	0.2444	481.8472	8m	28/03/19
2912	2184	49176	0.3674	367.6847	6m	27/03/19
2912	2184	70252	0.2907	450.8920	7m	17/02/19
2912	2184	91327	0.2254	418.1252	6m	28/03/19
2720	2040	49176	0.3538	789.3004	13m	23/03/19
2720	2040	70252	0.2767	444.2428	7m	24/02/19
2720	2040	91327	0.2101	394.3428	6m	22/03/19
2528	1896	49176	0.3404	336.0806	5m	21/03/19
2528	1896	70252	0.2625	539.5125	8m	17/02/19
2528	1896	91327	0.1962	597.7640	9m	22/03/19
2304	1728	49176	0.3227	577.1155	9m	19/03/19
2304	1728	70252	0.2352	581.6505	9m	17/02/19
2304	1728	91327	0.1664	358.1756	5m	21/03/19
2048	1536	49176	0.2928	707.3133	11m	07/03/19
2048	1536	70252	0.2023	576.9724	9m	17/02/19
2048	1536	91327	0.1344	401.3182	6m	07/03/19
1792	1344	49176	0.2497	534.6837	8m	05/03/19
1792	1344	70252	0.1638	618.8019	10m	17/02/19
1792	1344	91327	0.1033	606.1833	10m	16/03/19
1472	1104	49176	0.1909	647.5711	10m	05/03/19
1472	1104	70252	0.1064	587.9707	9m	17/02/19
1472	1104	91327	0.0596	631.3724	6m	05/03/19
1056	792	49176	0.0991	479.6345	7m	04/03/19
1056	792	70252	0.0457	402.9970	6m	10/02/19
1056	792	91327	0.0217	571.5584	9m	04/03/19
320	240	49176	0.0000	697.3579	11m	03/03/19
320	240	70252	0.0000	560.1663	9m	06/02/19
320	240	N/A	N/A	N/A	N/A	N/A

- Classifier with $O(\sqrt{n})$ bits:

Width	Height	Bits	MinPE	Seconds	Approx. Time	Date Finished
3072	2304	73764	0.2985	319.5296	5m	03/03/19
3072	2304	105378	0.2081	414.6347	6m	17/02/19
3072	2304	136991	0.1475	587.3197	9m	21/03/19
2912	2184	69922	0.2921	360.9533	6m	04/03/19
2912	2184	99889	0.2054	439.0349	7m	17/02/19
2912	2184	129856	0.1448	574.7981	9m	22/03/19
2720	2040	65312	0.2920	574.2693	9m	05/03/19
2720	2040	93303	0.2053	434.5565	7m	17/02/19
2720	2040	121294	0.1427	575.7162	9m	22/03/19
2528	1896	60702	0.2956	563.7625	9m	06/03/19
2528	1896	86717	0.2115	537.7033	8m	17/02/19
2528	1896	112732	0.1395	565.7045	9m	17/03/19
2304	1728	55323	0.2949	719.0057	11m	07/03/19
2304	1728	79033	0.2054	570.8157	9m	17/02/19
2304	1728	102743	0.1394	478.8804	7m	16/03/19
2048	1536	49176	0.2928	707.3133	11m	07/03/19
2048	1536	70252	0.2023	576.9724	9m	17/02/19
2048	1536	91327	0.1344	401.3182	6m	07/03/19
1792	1344	43029	0.2833	646.9333	10m	05/03/19
1792	1344	61470	0.1918	498.3309	8m	17/02/19
1792	1344	79911	0.1343	486.5471	8m	06/03/19
1472	1104	35345	0.2700	548.4453	9m	03/03/19
1472	1104	50493	0.1842	602.5947	10m	17/02/19
1472	1104	65641	0.1205	642.3130	6m	06/03/19
1056	792	25356	0.2476	1101.375	18m	03/03/19
1056	792	36223	0.1574	423.7316	7m	10/02/19
1056	792	47090	0.1053	636.2859	10m	16/03/19
320	240	7683	0.1428	730.9041	12m	03/03/19
320	240	10976	0.0674	480.4507	8m	10/02/19
320	240	14269	0.0320	598.0637	9m	03/03/19

- Classifier with $O(\log n \cdot \sqrt{n})$ bits:

Width	Height	Bits	MinPE	Seconds	Approx. Time	Date Finished
3072	2304	77762	0.2849	336.8287	5m	04/03/19
3072	2304	111089	0.1950	410.6305	6m	23/02/19
3072	2304	144416	0.1347	471.8878	7m	25/03/19
2912	2184	73212	0.2804	375.5300	6m	05/03/19
2912	2184	104589	0.1965	498.7603	8m	24/02/19
2912	2184	135966	0.1324	437.8727	7m	26/03/19
2720	2040	67790	0.2820	647.1747	6m	06/03/19
2720	2040	96843	0.1962	156.7496	2m	24/02/19
2720	2040	125895	0.1340	628.6887	10m	25/03/19
2528	1896	62410	0.2909	551.8320	9m	06/03/19
2528	1896	89158	0.2030	528.4735	8m	25/02/19
2528	1896	115905	0.1307	600.2269	10m	18/03/19
2304	1728	56194	0.2916	358.3991	5m	29/03/19
2304	1728	80278	0.2017	557.1894	9m	25/02/19
2304	1728	104361	0.1364	604.3428	10m	16/03/19
2048	1536	49176	0.2928	707.3133	11m	07/03/19
2048	1536	70252	0.2023	576.9724	9m	17/02/19
2048	1536	91327	0.1344	401.3182	6m	07/03/19
1792	1344	42261	0.2865	616.2887	10m	05/03/19
1792	1344	60373	0.1963	492.1460	8m	23/02/19
1792	1344	78485	0.1383	654.3639	10m	06/03/19
1472	1104	33785	0.2788	933.6181	15m	04/03/19
1472	1104	48264	0.1953	598.9760	9m	17/02/19
1472	1104	62744	0.1301	638.6556	10m	05/03/19
1056	792	23111	0.2721	1126.238	18m	03/03/19
1056	792	33016	0.1809	575.5981	9m	16/02/19
1056	792	42921	0.1277	623.7723	10m	04/03/19
320	240	5777	0.2037	800.3702	13m	03/03/19
320	240	8253	0.1268	703.0797	11m	16/02/19
320	240	10728	0.0714	568.4690	9m	03/03/19

- Classifier with $O(n)$ bits:

Width	Height	Bits	MinPE	Seconds	Approx. Time	Date Finished
3072	2304	110647	0.1960	838.7881	13m	18/03/19
3072	2304	158067	0.1170	579.8852	9m	27/02/19
3072	2304	205487	0.0714	328.6171	5m	29/03/19
2912	2184	99421	0.2099	512.1684	8m	25/03/19
2912	2184	142030	0.1233	507.3802	8m	26/02/19
2912	2184	184640	0.0727	441.9584	7m	29/03/19
2720	2040	86743	0.2234	331.2557	5m	24/03/19
2720	2040	123919	0.1367	605.8217	10m	27/02/19
2720	2040	161094	0.0841	490.3062	8m	26/03/19
2528	1896	74929	0.2439	446.1127	7m	16/03/19
2528	1896	107042	0.1551	356.6084	5m	27/02/19
2528	1896	139154	0.0930	530.5080	8m	18/03/19
2304	1728	62239	0.2667	653.6526	10m	17/03/19
2304	1728	88912	0.1729	593.4742	9m	27/02/19
2304	1728	115586	0.1118	601.5955	10m	18/03/19
2048	1536	49176	0.2928	707.3133	11m	07/03/19
2048	1536	70252	0.2023	576.9724	9m	17/02/19
2048	1536	91327	0.1344	401.3182	6m	07/03/19
1792	1344	37650	0.3137	622.1424	10m	06/03/19
1792	1344	53786	0.2252	557.5206	9m	26/02/19
1792	1344	69922	0.1650	711.2485	11m	07/03/19
1472	1104	25404	0.3385	503.1627	8m	04/03/19
1472	1104	36292	0.2655	568.3256	9m	25/02/19
1472	1104	47180	0.2003	737.7079	12m	05/03/19
1056	792	13074	0.3809	1114.103	18m	04/03/19
1056	792	18677	0.3237	473.9401	7m	17/02/19
1056	792	24281	0.2566	509.4404	8m	05/03/19
320	240	1200	0.4467	948.5706	15m	03/03/19
320	240	1715	0.4205	888.4257	14m	06/02/19
320	240	2229	0.3887	820.8869	13m	03/03/19