

CS498 Homework 6

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EM Topic models

For this problem, we used NIPS dataset from UCI machine learning repository. We first constructed a 1500×12419 data matrix from the dataset. The row number indicates the number of documents and the column indicates different words. Each cell is the number of count for that word in that document.

We need to cluster the 1500 documents into 30 topics. We used k-means algorithm to get the initials for \mathbf{p}_j and π_j . Both are not given directly, we got from some manipulations from the clustered labels we got from the k-means model result as shown in code.

For E-step, we used

$$p(\delta_{ij} = 1 \mid \theta^{(n)}, \mathbf{x}) = \frac{\left[\prod_k p_{j,k}^{x_{i,k}} \right] \pi_j}{\sum_l \left[\prod_k p_{l,k}^{x_{i,k}} \right] \pi_l}$$

to get a 1500×30 probability matrix which we can use for clustering documents.

For M-step, we updated

$$\mathbf{p}_j^{(n+1)} = \frac{\sum_i \mathbf{x}_i w_{ij}}{\sum_i \mathbf{x}_i^T \mathbf{1} w_{ij}}$$

and

$$\pi_j^{(n+1)} = \frac{\sum_i w_{ij}}{N}$$

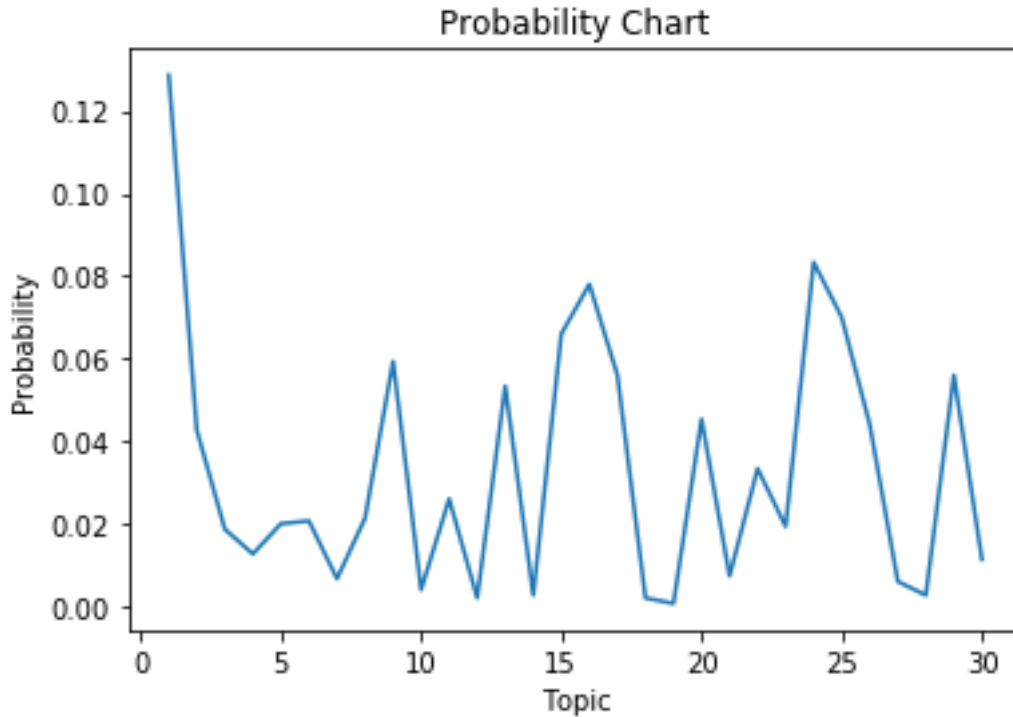
We ran 1000 times this algorithm and checked for Convergence by calculating $Q(\theta, \theta^{(n+1)}) - Q(\theta, \theta^{(n)})$. The expected likelihood with respect to δ is

$$Q(\theta, \theta^{(n)}) = \left(\sum_{ij} \left\{ \left[\sum_k x_{i,k} \log p_{j,k} \right] + \log \pi_j \right\} w_{ij} \right)$$

If it is smaller than the threshold we set, the algorithm stopped.

Note in order to deal with the underflow problem, We used expsumlog trick which can be found in the code. We also added some very small number and then scaled back if the word probability is 0.

Below is the graph of the probability with which the topic is selected



Below is the table for top ten frequent words for each topic.

##	Word 1	Word 2	Word 3	Word 4	Word 5	Word 6
## Topic 1	system	model	network	neural	function	input
## Topic 2	unit	network	input	learning	weight	hidden
## Topic 3	learning	action	model	task	control	reinforcement
## Topic 4	algorithm	vector	function	learning	loss	class
## Topic 5	network	unit	input	hidden	output	learning
## Topic 6	weight	network	error	training	set	input
## Topic 7	network	task	neural	learning	training	architecture
## Topic 8	input	network	output	neural	noise	function
## Topic 9	network	training	set	data	neural	error
## Topic 10	classifier	training	network	rbf	set	error
## Topic 11	word	network	recognition	training	system	model
## Topic 12	cell	head	direction	rat	model	angular
## Topic 13	model	data	network	set	neural	parameter
## Topic 14	character	field	system	window	network	input
## Topic 15	data	model	algorithm	set	parameter	point
## Topic 16	network	neural	system	input	function	learning
## Topic 17	learning	algorithm	function	problem	policy	action
## Topic 18	hint	learning	examples	function	error	market
## Topic 19	monte	carlo	player	decision	policy	base
## Topic 20	object	image	network	images	model	recognition
## Topic 21	function	threshold	network	weight	neural	input
## Topic 22	function	set	training	vector	algorithm	error
## Topic 23	speech	network	system	model	input	signal
## Topic 24	function	network	algorithm	learning	neural	model
## Topic 25	cell	model	input	neuron	visual	field
## Topic 26	neuron	network	input	model	neural	synaptic
## Topic 27	david	michael	john	richard	peter	author

## Topic 28	eeg	component	response	trial	artifact	ica
## Topic 29	learning	network	error	weight	training	input
## Topic 30	model	learning	control	movement	motor	forward
##	Word 7	Word 8	Word 9	Word 10		
## Topic 1	signal	output	circuit	information		
## Topic 2	layer	output	pattern	function		
## Topic 3	robot	function	system	states		
## Topic 4	set	weight	bound	problem		
## Topic 5	function	training	pattern	weight		
## Topic 6	noise	generalization	function	learning		
## Topic 7	control	solution	input	problem		
## Topic 8	training	set	data	information		
## Topic 9	input	output	unit	learning		
## Topic 10	neural	problem	center	gaussian		
## Topic 11	speech	hmm	neural	set		
## Topic 12	system	velocity	mcnaughton	neural		
## Topic 13	learning	algorithm	training	function		
## Topic 14	net	set	word	training		
## Topic 15	learning	distribution	method	function		
## Topic 16	weight	output	model	unit		
## Topic 17	system	optimal	model	result		
## Topic 18	performance	method	information	network		
## Topic 19	move	rollout	network	trial		
## Topic 20	view	system	set	feature		
## Topic 21	circuit	size	number	result		
## Topic 22	kernel	data	problem	classifier		
## Topic 23	recognition	neural	output	information		
## Topic 24	input	problem	set	data		
## Topic 25	cortex	orientation	response	network		
## Topic 26	system	function	learning	firing		
## Topic 27	index	thomas	eric	paul		
## Topic 28	data	single	visual	erp		
## Topic 29	function	algorithm	neural	set		
## Topic 30	field	arm	dynamic	trajectory		

Image segmentation using EM

For this problem, we segmented images using a clustering method. We were given 3 images and we need to segment these three images to 10, 20, 50 segments. For the sunset image, we need to segment using five different start points. Thus, for this problem, we had 13 images within the report.

They are

- “A goby on its nest” 10, 20, 50 segments version
- “A strelitzia” 10, 20, 50 segments version
- “Sunset”, 10, 20(5 different start points), 50 segments version

I will use “Sunset” image as an example to explain the methods we used. The “Sunset” image is a 330×600 corresponding to height and width image. Each location of the image has a pixel data which contains 3 pixel numbers representing red, green and blue, aka RGB. We formed a dataset of pixel using these data. The dimension of the data is $(330 \times 600 = 198000, 3)$. Then we did normarlization so that each feature of the data has a 0 mean and a 1 standard deviation.

We used cluster centers as initial values for the means and the fraction of points in each cluster as mixture weight initials where we got from k-means algorithm.

For E-step, We firstly calculated

$$p_{(\delta_{ij}=1 | \theta^{(n)}, \mathbf{x})} = \frac{[\exp(-\frac{1}{2}(\mathbf{x}_i - \mu_j)^T(\mathbf{x}_i - \mu_j))]\pi_j}{\sum_k [\exp(-\frac{1}{2}(\mathbf{x}_i - \mu_j)^T(\mathbf{x}_i - \mu_j))]\pi_k} = w_{ij}$$

Then we updated μ and π at M-step based on

$$\mu_j^{(n+1)} = \frac{\sum_i x_i w_{ij}}{\sum_i w_{ij}}$$

and

$$\pi_j^{(n+1)} = \frac{\sum_i w_{ij}}{N}$$

After updating, we calculated the expected likelihood with respect to δ which is

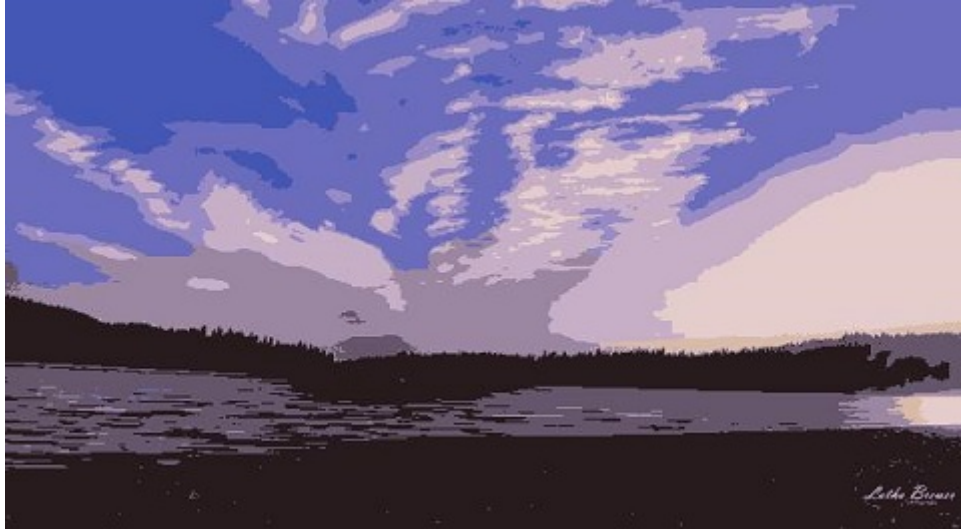
$$Q_{(\theta; \theta^{(n)})} = \left(\sum_{ij} \left\{ \left[-\frac{1}{2}(\mathbf{x}_i - \mu_j)^T(\mathbf{x}_i - \mu_j) \right] + \log(\pi_j) \right\} w_{ij} + K \right)$$

Because of the fairly large computation, We tried to run the algorithm 100 times and set a threshold of 0.0001. If the difference between (Q^n, Q^{n+1}) is smaller than this number, we stopped the alogrithm.

We then replaced the original pixel data by the pixel from μ with the highest value of the posterior probability for that pixel. For example, for all first segment pixel data, we changed the pixel to μ_1 , so on and so forth.

Our final result is below

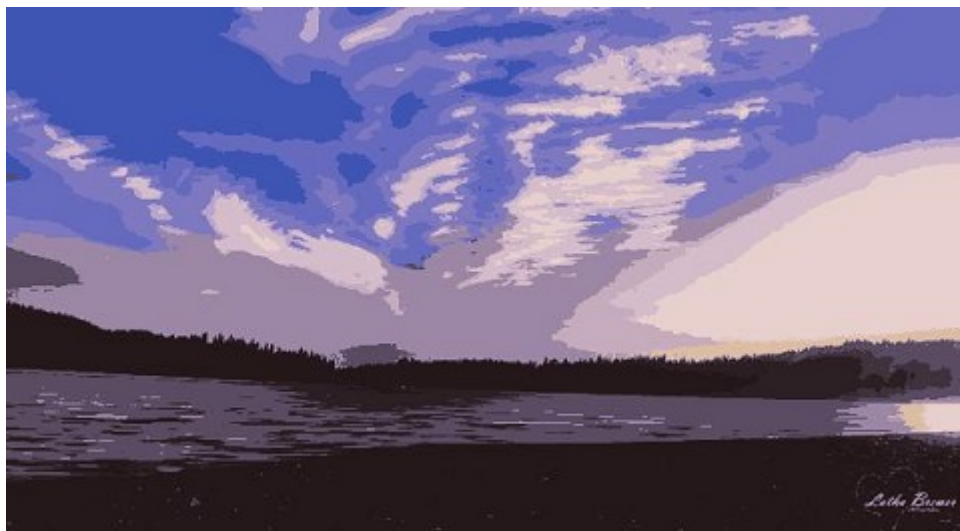
Sunset 10 segments



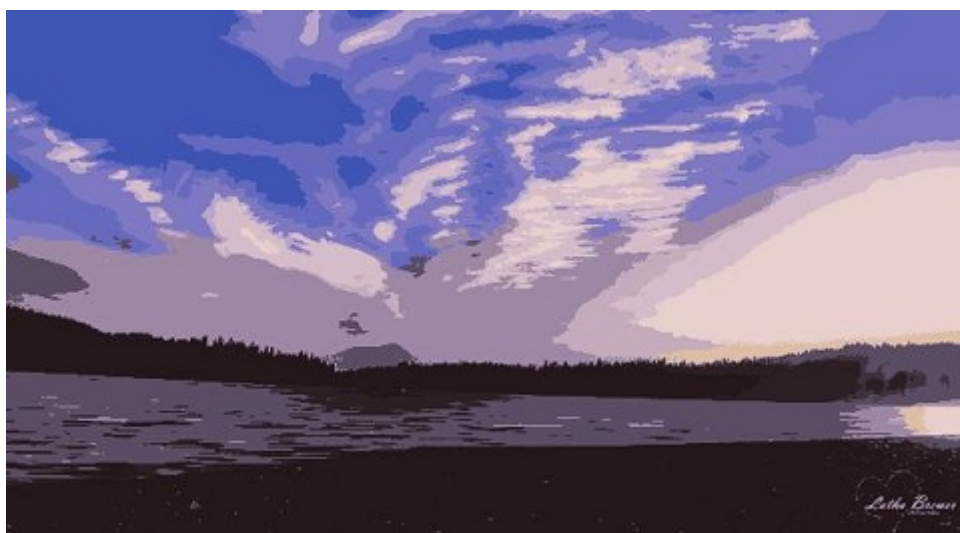
Sunset 10 segments

We used k-means algorithm to produce 5 different start points by setting different seeds. We produced the following five pictures. We can observe that basically these pictures are the same, it is hard to find any differences.

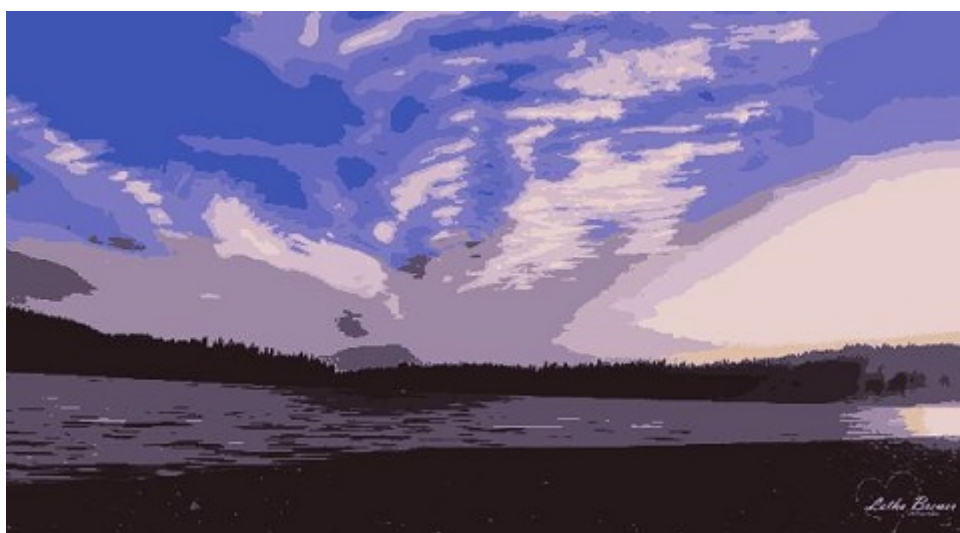
Sunset 20 segments



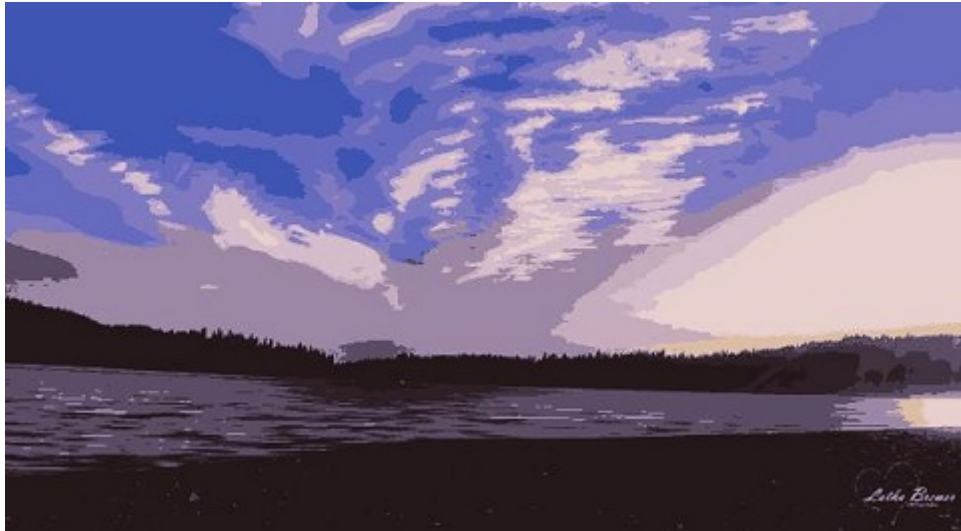
Sunset 20 segments, seed = 25



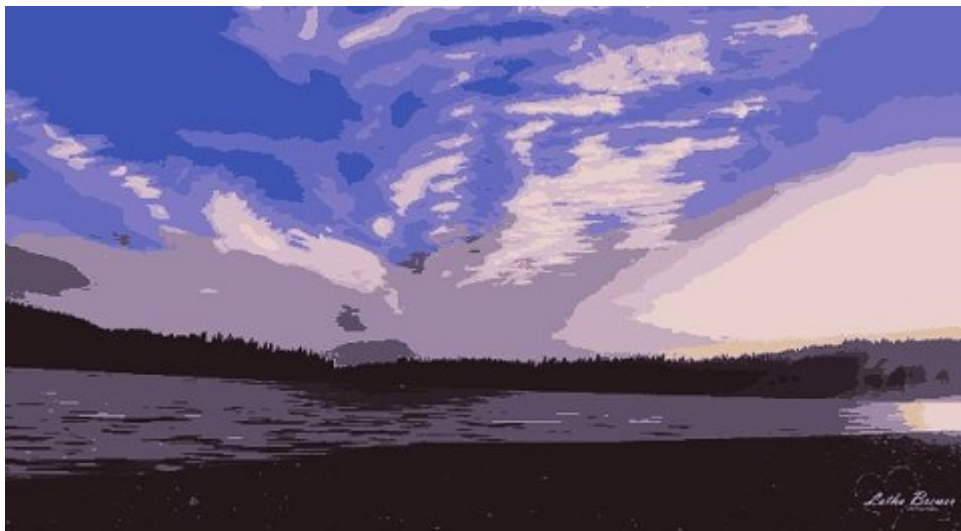
Sunset 20 segments, seed = 33



Sunset 20 segments, seed = 37



Sunset 20 segments, seed = 75



Sunset 20 segments, seed = 83

Sunset 50 Segments



Sunset 50 segments

Flower 10 segments



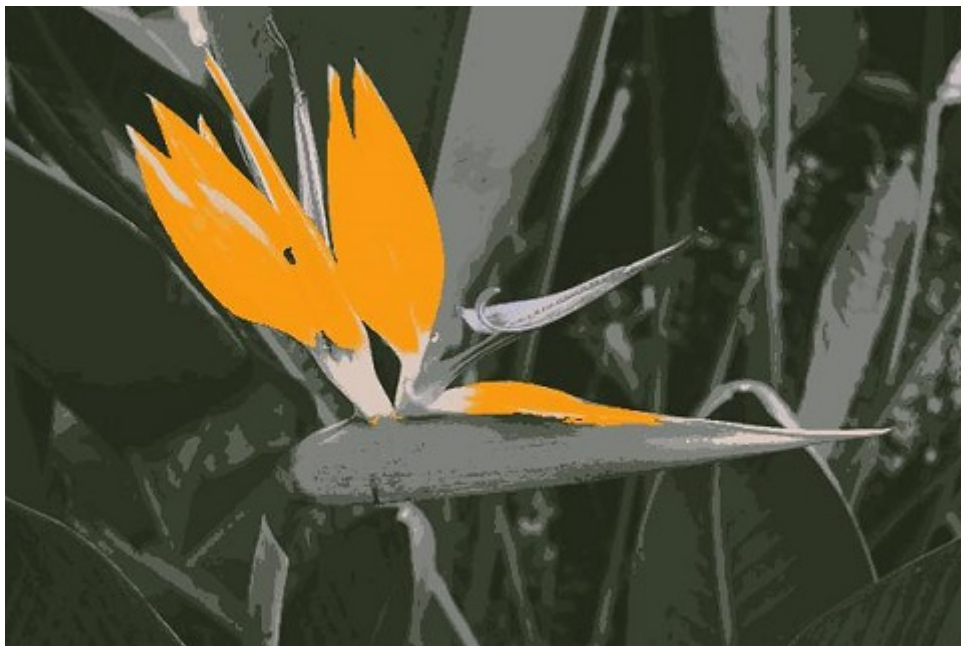
Flower 10 segments

Flower 20 segments



Flower 20 segments

Flower 50 segments



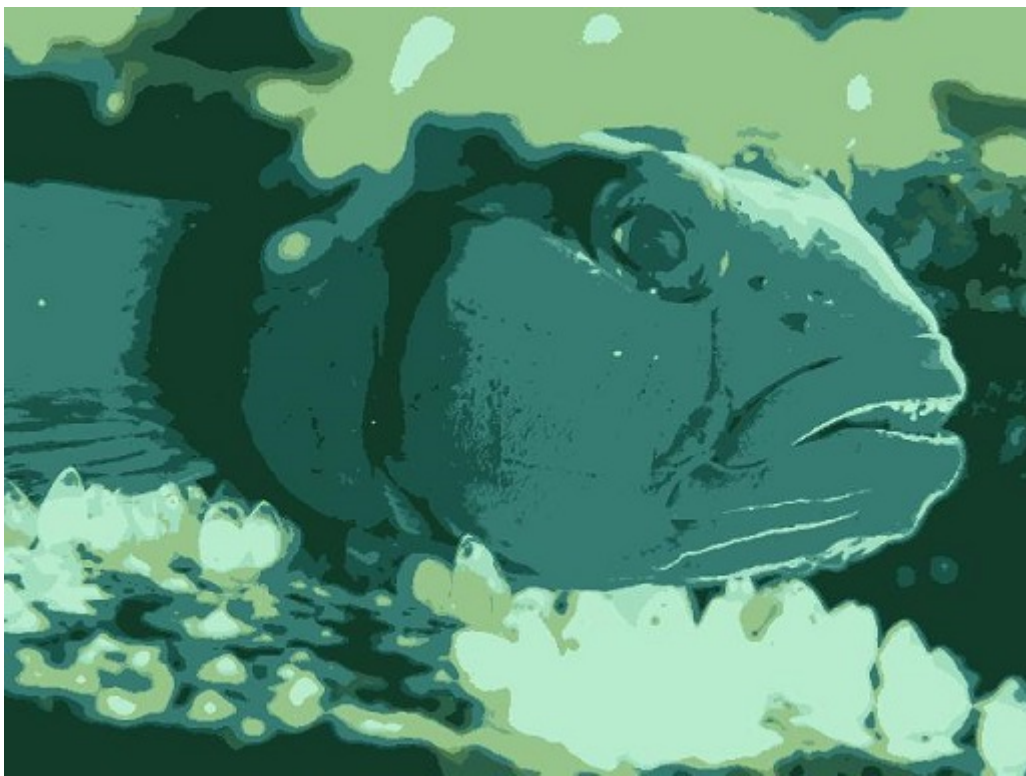
Flower 50 segments

Fish 10 segments



Fish 10 segments

Fish 20 segments



Fish 20 segments

Fish 50 segments



Fish 50 segments