Stage 2: Exploratory Data Analysis

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EDA Main Report

Introduction

Our project plans to look into trend in animal treatment in Dallas animal shelters. Using a dataset containing information on all recent animals brought into the shelter, we are going to try to answer some of the following questions. What traits affect a dog's probability of adoption? Are there seasonal trends in the adoption of different animals? Are animals who enter the animal shelter with chips more likely to be returned to their owner? On the table below, you can see some of the variables we are working with in the dataset.

Dogs

Dogs are the most common animal winding up in the animal shelters which form our dataset. From our total of 44,194 dogs, 35% were adopted, 30% were returned to owners, 16% were transferred, and 15% were euthanized. The most common breed of dog in our dataset is the pit bull, with 10,033 being admitted to animal shelters in between 10/01/2017 and 04/03/2019. We are especially interested in how pit bulls are treated within our datasets as these dogs have an infamous reputation of being overly aggressive. Is it possible that this reputation results in a lower adoption rate for pit bulls that other breeds?

Pit bulls

To look into how pit bulls are handled within animal shelters, we decided to explore how the outcomes of pit bulls may differ from non-pitbulls. Table 1 describes the differences in outcome rates for non-pitbulls compared to pitbulls.

Table 1: Pitbull Outcomes

Outcome	Pitbull (%)	Non-Pitbull (%)
Adoption	32.10	36.04
Euthanized	28.67	10.43
Returned to owner	22.03	31.01
Transfer	10.98	17.74
Foster	2.16	1.57
Other	1.83	0.99
Dead on arrival	0.88	0.83
Treatment	0.79	0.95
Died	0.52	0.39
Missing	0.04	0.06

We see that pit bulls, while only adopted at a slightly lower rate (~5%), are euthanized at well over double the rate of other dogs. Further, we see that other dogs have a much higher chance of being transferred to another facility or returned to their owner. It would be valuable to get a better understanding of this relationship, but we likely need to control for things like chip status and intake condition. Moving forward we would like to look into some binomial regression to look into the outcomes of pit bulls. To do this we plan to make a more general outcome variable of Dead or Alive status (to reduce the dimension of the current `outcome_type` variable). In fitting this model, we plan to control for intake status (with which we still need to do some work on string analysis), chip status, and month.

Dogs vs Cats

In Minnesota and Iowa, our home states, animal shelters often report having more difficulty dealing with stray cats. There are lots of problems that feral cats cause including environmental damage and spread of disease. We were interested if we can see these kinds of differences in our data. Do cats spend longer in animal shelters? Are they euthanized at higher rates? To describe some of these differences we looked we created a summary graph of different characteristics of dogs and cats. Since our dataset contains observations of 44194 dogs and only 12891 cats, we created this chart in terms of proportion of each animal matching a certain criterion.

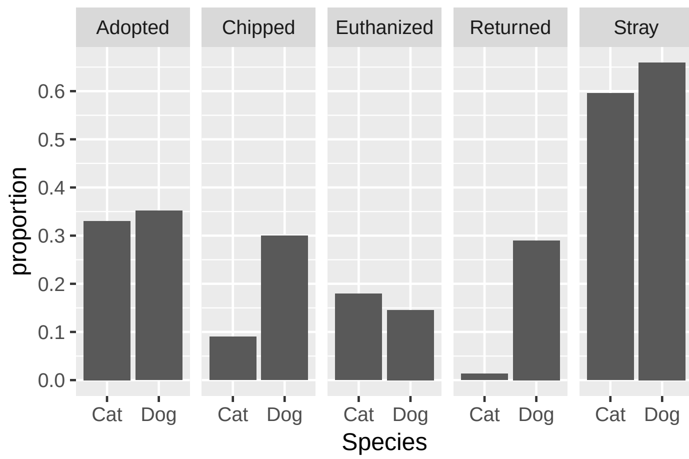


Figure 1: Cat vs Dog Characteristics

Interestingly enough, we see that the difference between proportions of cats and dogs adopted is not very pronounced. A slightly lower percentage of cats are adopted and a slightly higher percent of cats are euthanized compared to dogs. However, we do see that very few cats entering humane societies have scannable chips, and an even lower proportion are returned to their owner. Additionally, it seems appears that fewer cats are brought into the shelter as strays. We may use this data to do another binomial analysis to piece apart differences between cat and dog adoptions. We may do a similar thing as the pit bull analysis with the creation of a dead or alive outcome variable. We would want to consider controlling for in this analysis would be breed, intake condition, and chip status.

Time of Year

Another question that we had in our Stage 1 report was what seasonal trends exists in adoptions. One could imagine a situation where more puppies are adopted in December or more rabbits are adopted in early spring. To explore this, we did some plotting to see how many animals were adopted in each month.

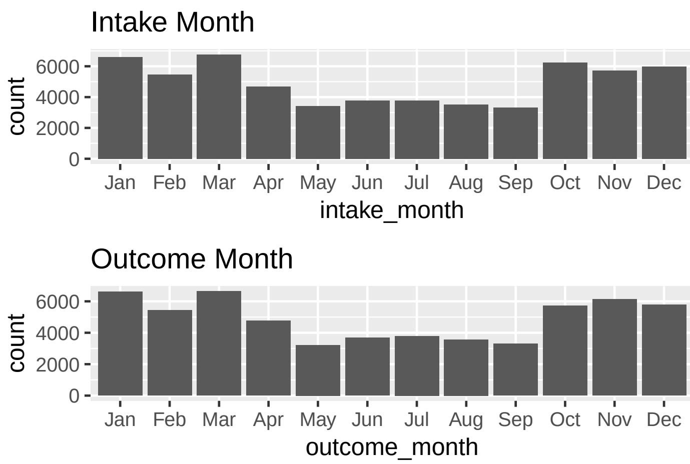


Figure 2: Animal Adoptions by Month

These trends surprised us. We see a large drop in adoptions during the summer but a spike in the fall, winter, and early spring. These trends were true for both Dog and Cat adoptions (see appendix). For rabbits, many were adopted in February and July. While we are unable to put together a rigorous defense for why these trends are occurring, we see that we may need to control for it in our binomial analysis.

Rehabilitable

Many animals coming into the animal shelter may be in bad shape. Because of this, euthanasia may be the best outcome for the animal. In our data, the `intake_subtype` variable summarizes the condition of the animals coming into the shelter. This variable is in the form of a string with 3 descriptors. We are in the midst of using a string analysis to take out relevant information. One key word that appeared in many of the observations was "REHABILITABLE". It is logical that animals which come in in better condition and show promise of getting better are less likely to be euthanized. We may want to adjust for this in our binomial analysis.

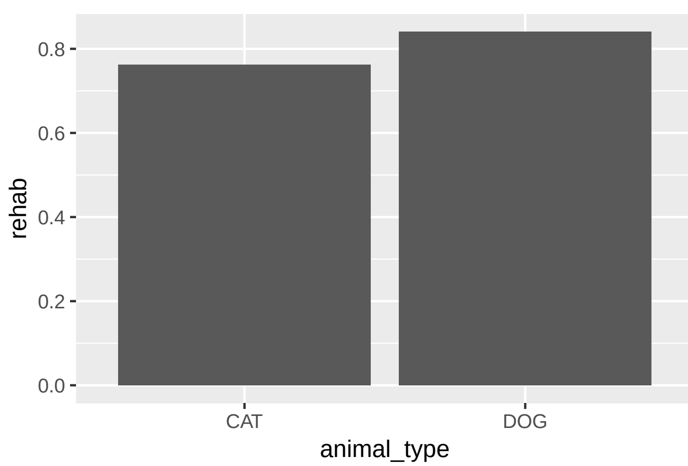


Figure 3: Intake Status in Cats and Dogs

From this plot we can see that a higher proportion of dogs (85%) come in with rehabilitable compared to 76% of cats. This information could be used in our comparison of cats and dogs. In the coming weeks we plan to dig more into this variable and consult a current vet-med student to learn more about what these key words indicate.

Annotated Appendix and References

Variables

Table 2: Description of Variables

Variable Name	Variable Role	Variable Type	Range of Values	Units
animal_breed	explanatory	categorical	296 unique breeds	NA
animal_origin	explanatory	categorical	4 sources of shelter animals	NA
animal_type	explanatory	categorical	5 species of animal	NA
chip_status	explanatory	bianary	(0,1)	NA
intake_type	potential confounder	categorial	how animal came to be at the shelter	NA
outcome_type	reponse	categorial	how animals was removed from shelter	NA
intake_condition	potential confounder	categorial	keyword description of animal status at intake	NA
outcome_condition	potential confounder	categorial	keyword description of animal status at outcome	NA
intake_date	response	date	(2017-10-01, 2019-04-03)	y-m-d
outcome_date	response	date	(2017-10-01, 2019-04-03)	y-m-d

Citations

1. Lepper, M., Kass, P. H., & Hart, L. A. (2002). Prediction of adoption versus euthanasia among dogs and cats in a California animal shelter. Journal of Applied Animal Welfare Science, 5(1), 29-42.

2. Posage, J. M., Bartlett, P. C., & Thomas, D. K. (1998). Determining factors for successful adoption of dogs from an animal shelter. Journal of the American Veterinary Medical Association, 213(4), 478-482.

3. Lampe, R., & Witte, T. H. (2015). Speed of dog adoption: Impact of online photo traits. Journal of applied animal welfare science, 18(4), 343-354.

Interesting Stories in our data

In the wild, there are badgers. Therefore, it makes sense that now and then a animal shelter would occasionally encounter a rouge badger that ended up in the wrong neighborhood. However, this is not what we expected:

```
## # A tibble: 1 x 3
##   animal_breed animal_origin outcome_type
##   <chr>        <chr>         <chr>
## 1 BADGER       FIELD         RETURNED TO OWNER
```

You'll find them on the beaches soaking in the rays, but rarely do you find them in a Dallas animal shelter.

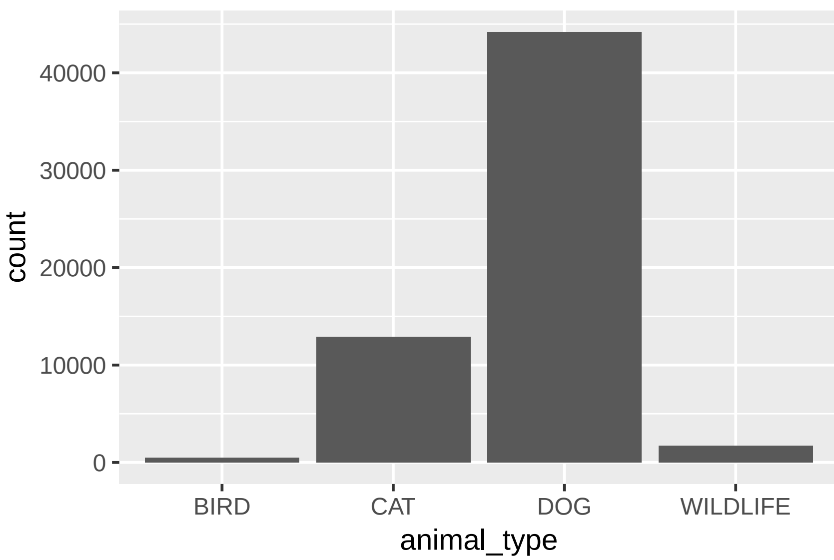
```
## # A tibble: 1 x 4
##   animal_type animal_origin    animal_breed outcome_type
##   <chr>       <chr>            <chr>        <chr>
## 1 WILDLIFE    OVER THE COUNTER CALIFORNIAN  ADOPTION
```

Exploring animal_type

```r
# animal type
adoptions %>%
  group_by(animal_type) %>%
  count(sort = TRUE)
```

```
## # A tibble: 6 x 2
## # Groups:   animal_type [6]
##   animal_type     n
##   <chr>       <int>
## 1 DOG         44194
## 2 CAT         12891
## 3 WILDLIFE     1696
## 4 BIRD          485
## 5 LIVESTOCK      33
## 6 D               1
```

```r
adoptions %>%
  filter(!animal_type%in%c("D", "LIVESTOCK")) %>%
  ggplot(aes(x=animal_type))+
  geom_bar()
```



We see that most observations in our dataaset were of dogs, followed by cats. It seems there is 1 mislabeled dog which we will take care of in our data cleaning file.

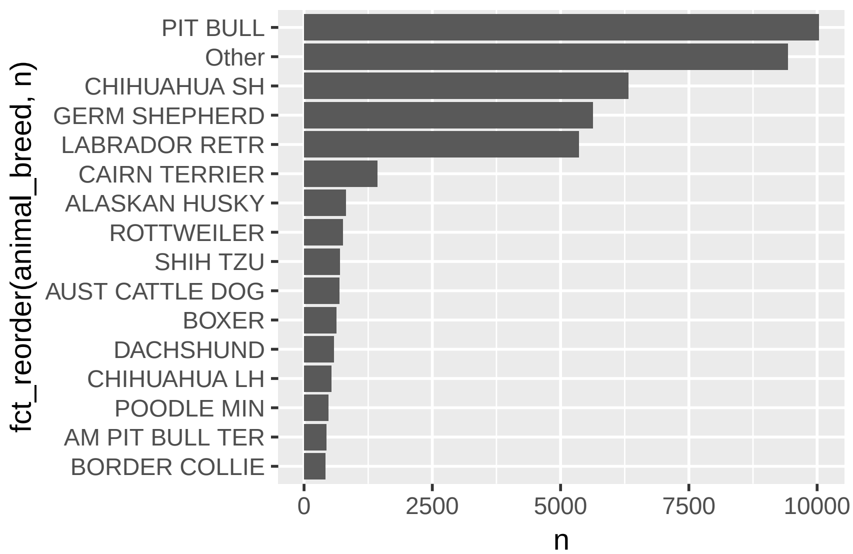
Exploring animal_breed

```r
## Which dog breeds are in our data?
adoptions %>%
  filter(animal_type == "DOG") %>%
  mutate(animal_breed = fct_lump(animal_breed, n=15)) %>%
  group_by(animal_breed) %>%
  count(sort = TRUE)
```

```
## # A tibble: 16 x 2
## # Groups:   animal_breed [16]
```

```
##    animal_breed         n
##    <fct>            <int>
##  1 PIT BULL         10033
##  2 Other             9423
##  3 CHIHUAHUA SH      6322
##  4 GERM SHEPHERD     5625
##  5 LABRADOR RETR     5353
##  6 CAIRN TERRIER     1430
##  7 ALASKAN HUSKY      812
##  8 ROTTWEILER         751
##  9 SHIH TZU           696
## 10 AUST CATTLE DOG    683
## 11 BOXER              629
## 12 DACHSHUND          581
## 13 CHIHUAHUA LH       528
## 14 POODLE MIN         476
## 15 AM PIT BULL TER    433
## 16 BORDER COLLIE      419
```

```r
adoptions %>%
  filter(animal_type == "DOG") %>%
  mutate(animal_breed = fct_lump(animal_breed, n=15)) %>%
  group_by(animal_breed) %>%
  count(sort = TRUE)%>%
  ggplot(aes(x=fct_reorder(animal_breed,n), y=n))+
  geom_bar(stat="identity")+
  coord_flip()
```

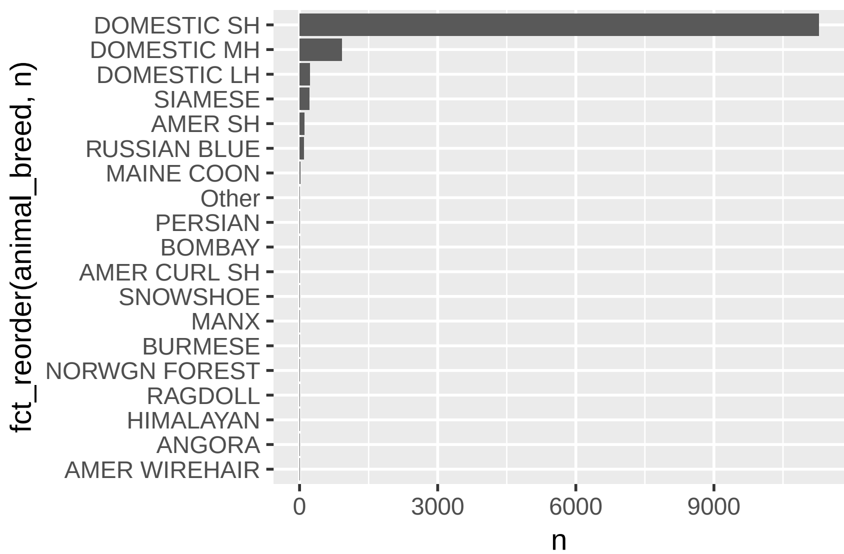


We have a huge variety of dog breeds in our data. The most common breed is the pit bull, which we are planning to use for our analysis. There are many other dog breeds that are seen as aggressive (rottweilers and boxers) that we may make into a new variable `aggressive`.

```r
## Which cat breeds are in our data?
adoptions %>%
  filter(animal_type == "CAT") %>%
  mutate(animal_breed = fct_lump(animal_breed, n=10)) %>%
  group_by(animal_breed) %>%
  count(sort = TRUE)
```

```
## # A tibble: 11 x 2
## # Groups:   animal_breed [11]
##    animal_breed     n
##    <fct>        <int>
##  1 DOMESTIC SH  11273
##  2 DOMESTIC MH    916
##  3 DOMESTIC LH    219
##  4 SIAMESE        214
##  5 AMER SH        101
##  6 RUSSIAN BLUE    96
##  7 Other           33
##  8 MAINE COON      19
##  9 PERSIAN          8
## 10 AMER CURL SH     6
## 11 BOMBAY           6
```

```r
adoptions %>%
  filter(animal_type == "CAT") %>%
  mutate(animal_breed = fct_lump(animal_breed, n=15)) %>%
  group_by(animal_breed) %>%
  count(sort = TRUE)%>%
  ggplot(aes(x=fct_reorder(animal_breed,n), y=n))+
  geom_bar(stat="identity")+
  coord_flip()
```



Almost all of the cats in our data were domestic short hair cats.

```r
## Which types of wildlife are in our data?
adoptions %>%
  filter(animal_type == "WILDLIFE") %>%
  mutate(animal_breed = fct_lump(animal_breed, n=10)) %>%
  group_by(animal_breed) %>%
  count(sort = TRUE)
```

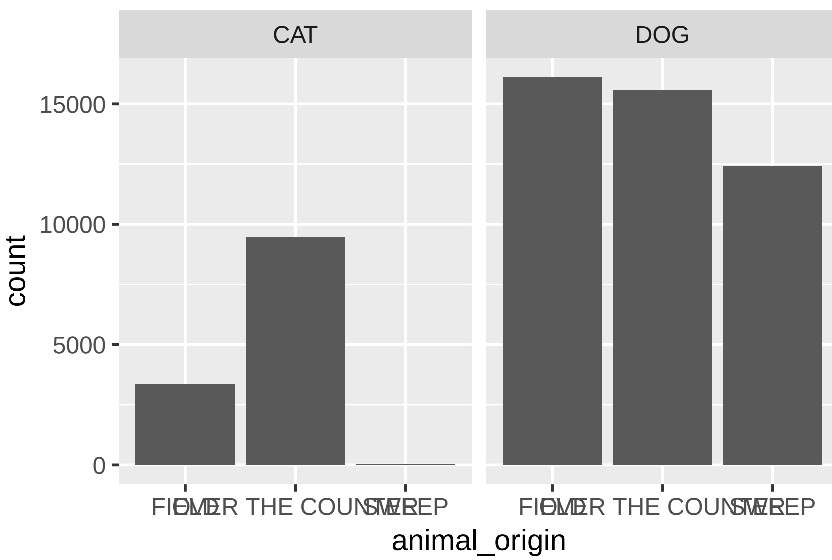
```
## # A tibble: 11 x 2
## # Groups:   animal_breed [11]
```

```
##    animal_breed     n
##    <fct>        <int>
##  1 RACCOON        471
##  2 OPOSSUM        404
##  3 TURTLE         190
##  4 GUINEA PIG     148
##  5 RABBIT SH      136
##  6 HAMSTER         98
##  7 SQUIRREL        82
##  8 Other           68
##  9 BAT             59
## 10 FOX             23
## 11 SKUNK           17
```

This variable is more for fun. Look at all these fun creatures they get to deal with at the animal shelter. We are kind of interested in rabbits so we will talk about that later.

Exploring animal origin

```r
adoptions %>%
  filter(dog == 1 | cat == 1) %>%
  filter(!is.na(animal_origin)) %>%
  ggplot(aes(x=animal_origin))+
  geom_bar()+
  facet_grid(~animal_type)
```

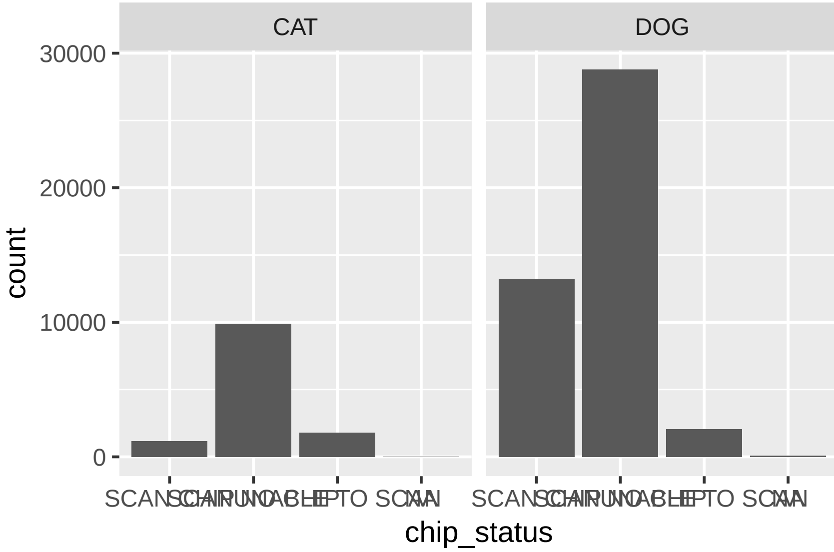


Dogs and cats can come from 3 possible origins: field, over the counter, and sweep. As of this moment, we are not sure what the difference between field and sweep are. However, it is interesting that only dogs are brought in from sweeps.

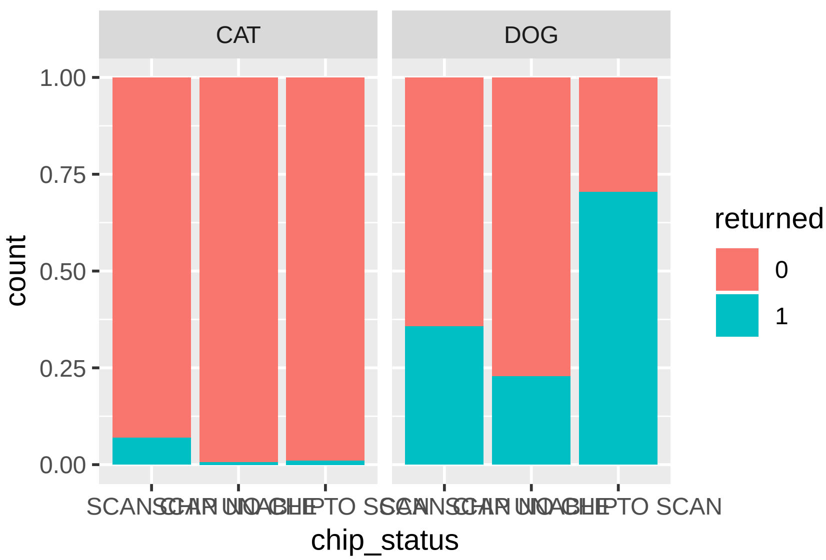
Exploring chip status

```r
## General distribution of variable
adoptions %>%
  filter(dog == 1 | cat == 1) %>%
  ggplot(aes(x=chip_status))+
```

```r
  geom_bar()+
  facet_grid(~animal_type)
```




```r
## Relationship with returned to owner status
adoptions %>%
  filter(dog == 1 | cat == 1) %>%
  filter(!is.na(chip_status)) %>%
  mutate(returned = as.factor(ifelse(outcome_type== "RETURNED TO OWNER", 1, 0))) %>%
  ggplot(aes(x=chip_status, fill = returned))+
  geom_bar(position = "fill")+
  facet_grid(~animal_type)
```



We see that most cats and dogs do not have chips. However, a larger proportion of dogs have chips than cats. A higher proportion of dogs are returned to owners than cats in all three categories of chip status.

Exploring intake_subtype

```
## Which dog breeds are in our data?
adoptions %>%
  mutate(intake_subtype = fct_lump(intake_subtype, n=10)) %>%
  group_by(intake_subtype) %>%
  count(sort = TRUE)
```

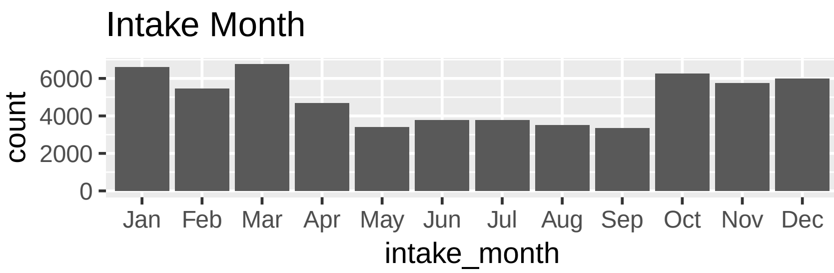
```
## # A tibble: 11 x 2
## # Groups:   intake_subtype [11]
##    intake_subtype          n
##    <fct>               <int>
##  1 AT LARGE            28889
##  2 GENERAL             15495
##  3 CONFINED             5598
##  4 POSSIBLY OWNED       2085
##  5 Other                1813
##  6 QUARANTINE           1454
##  7 RETURN30             1312
##  8 INJURED               972
##  9 KEEP SAFE             781
## 10 UNINJURED             474
## 11 EUTHANASIA REQUESTED  427
```

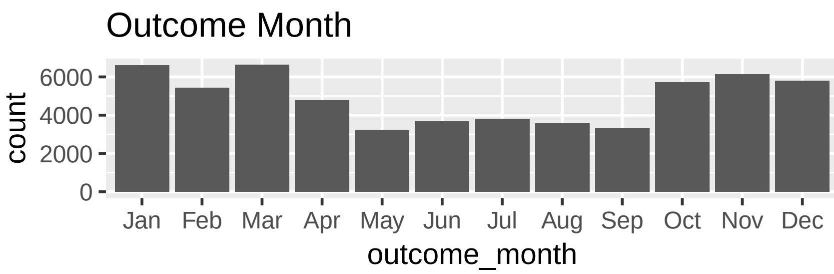
This general intake listing does not give us a lot of infomration. However, we do see that a few animals may have been returned (non-independent observation), and some animals are requested to be euthanized upon admission.

Exploring intake_date and outcome_date

```
intake <- adoptions %>%
  mutate(intake_month = month(intake_date, label = TRUE)) %>%
  ggplot(aes(x=intake_month))+
  geom_bar()+
  ggtitle("Intake Month")

outcome <- adoptions %>%
  filter(!is.na(outcome_date)) %>%
  mutate(outcome_month = month(outcome_date, label = TRUE)) %>%
  ggplot(aes(x=outcome_month))+
  geom_bar()+ ggtitle("Outcome Month")
gridExtra::grid.arrange(intake, outcome)
```

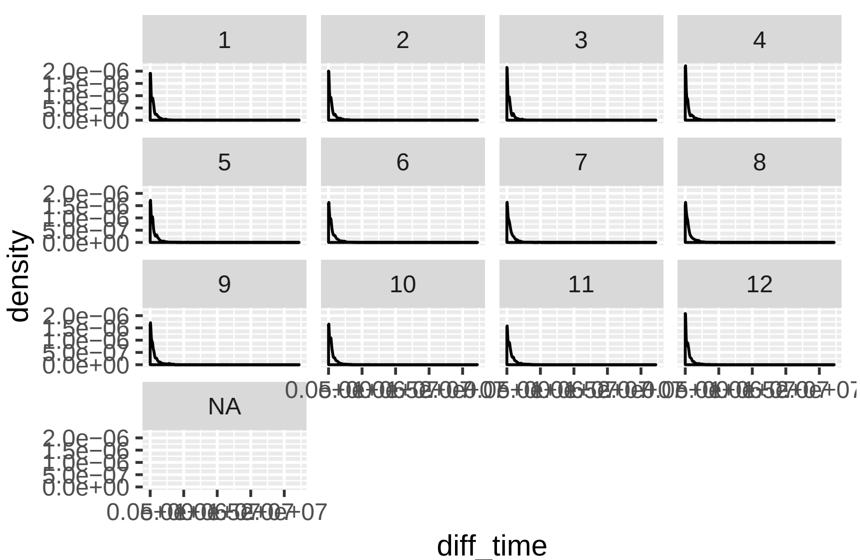





```
# Ammount of time spent at the humane society looks to be about the same from month to month.

adoptions %>%
  mutate(diff_time=difftime(outcome_date, intake_date))%>%
  select(diff_time, month)%>%
  ggplot(aes(x=diff_time))+
  geom_density()+
  facet_wrap(~as.factor(month))
```

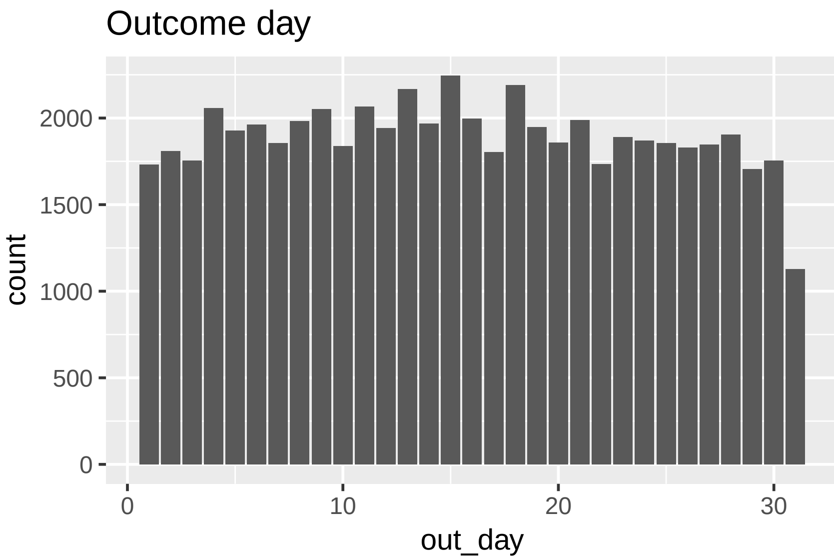
```
## Don't know how to automatically pick scale for object of type difftime. Defaulting to continuous.
## Warning: Removed 642 rows containing non-finite values (stat_density).
```



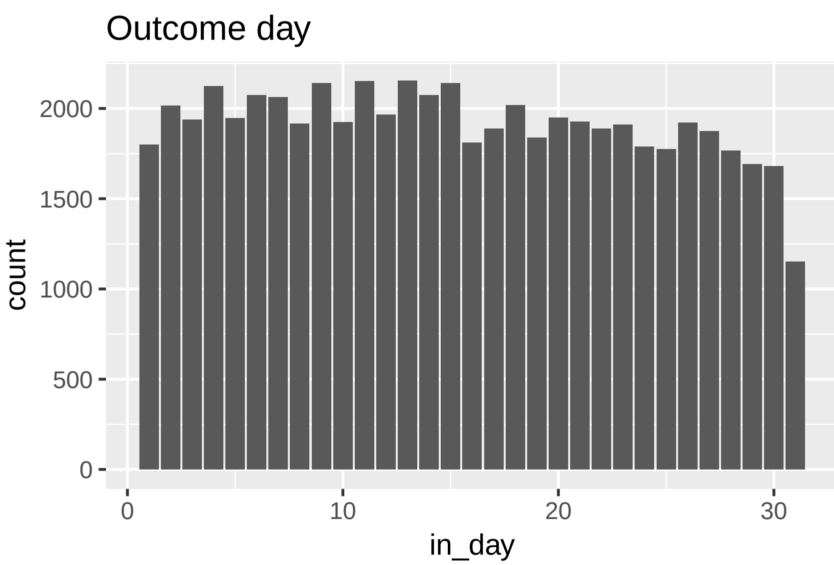
Differences in income day

```
adoptions%>%
  mutate(out_day=day(outcome_date))%>%
  ggplot(aes(x=out_day))+
  geom_bar()+ ggtitle("Outcome day")
```

```
## Warning: Removed 642 rows containing non-finite values (stat_count).
```

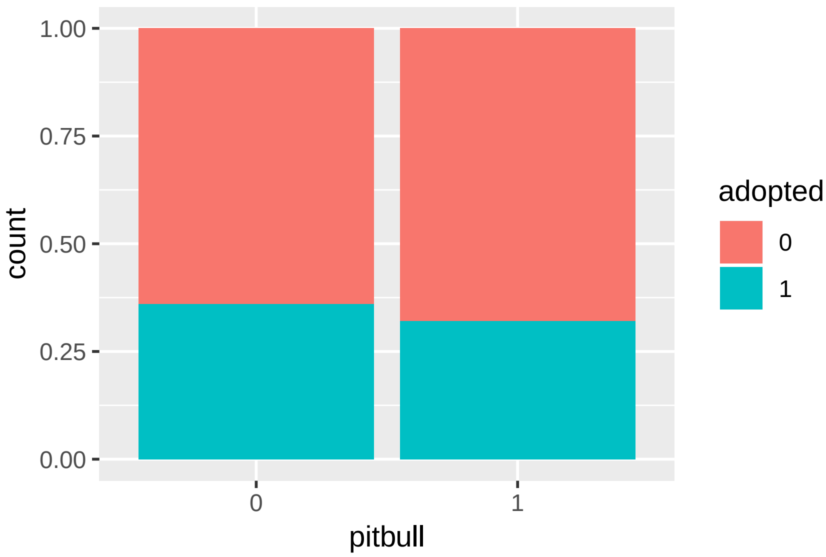



```
adoptions%>%
  mutate(in_day=day(intake_date))%>%
  ggplot(aes(x=in_day))+
  geom_bar()+ ggtitle("Outcome day")
```



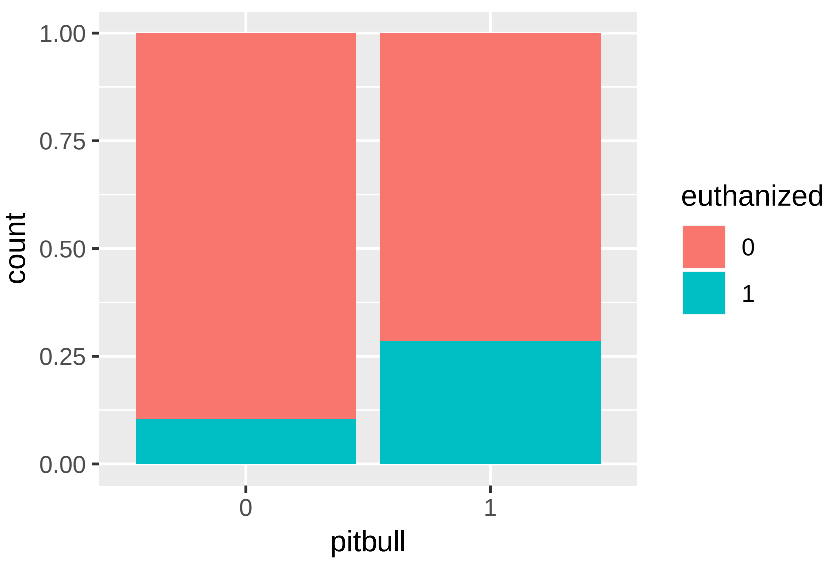
Pitbulls and Adoptions

```
adoptions %>%
  filter(dog == 1) %>%
  mutate(adopted = as.factor(adopted),
         pitbull = as.factor(pitbull)) %>%
  ggplot(aes(x = pitbull, fill = adopted))+
  geom_bar(position = "fill")
```



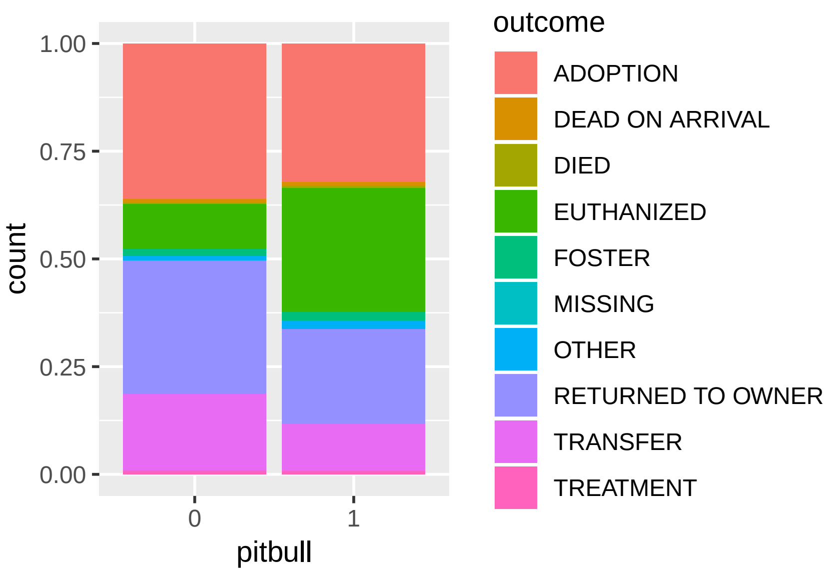
There does not seem to be a large difference between the adoption rates of pitbull and non-pitbulls. We should try and filter out some of the non-adopted dogs though, not all dogs come to the shelter to be adopted.

```r
adoptions %>%
  filter(dog == 1) %>%
  mutate(euthanized = as.factor(euthanized),
         pitbull = as.factor(pitbull)) %>%
  ggplot(aes(x = pitbull, fill = euthanized))+
  geom_bar(position = "fill")
```



While pitbulls are not adopted at a higher rate, the are euthanized at a higher rate than other dogs. Let's look at all possible outcomes to see how this is possible.

```r
adoptions %>%
  filter(dog == 1) %>%
  mutate(outcome = as.factor(outcome_type),
         pitbull = as.factor(pitbull)) %>%
  ggplot(aes(x = pitbull, fill = outcome))+
  geom_bar(position = "fill")
```




```
adoptions %>%
  filter(dog == 1) %>%
  mutate(outcome = as.factor(outcome_type),
         pitbull = as.factor(pitbull)) %>%
  group_by(pitbull, outcome_type) %>%
  count() %>%
  rename("freq"=n)%>%
  group_by(pitbull)%>%
  mutate(freq = freq/ sum(freq))%>%
  spread(outcome_type,freq)
```

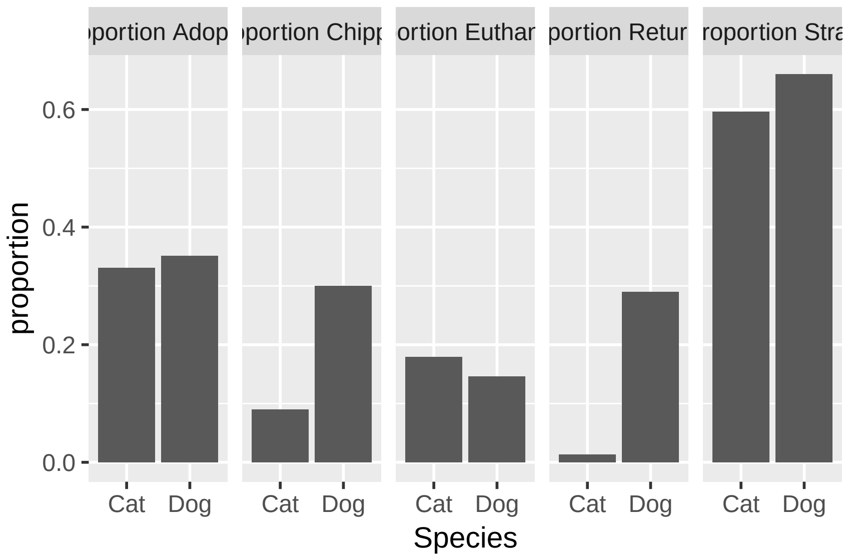
```
## # A tibble: 2 x 11
## # Groups:   pitbull [2]
##   pitbull ADOPTION `DEAD ON ARRIVA~    DIED EUTHANIZED FOSTER MISSING
##   <fct>      <dbl>            <dbl>   <dbl>      <dbl>  <dbl>   <dbl>
## 1 0          0.360          0.00831 0.00386      0.104 0.0157 6.15e-4
## 2 1          0.321          0.00877 0.00518      0.287 0.0216 3.99e-4
## # ... with 4 more variables: OTHER <dbl>, `RETURNED TO OWNER` <dbl>,
## #   TRANSFER <dbl>, TREATMENT <dbl>
```

A far higher percentage of pitbulls are euthanized than other breeds. Other dogs are adopted, returned to owners, and trasfered at a higher rate.

Differences between dogs and cats

```
adoptions %>%
  filter(dog == 1 | cat == 1) %>%
  mutate(Species = ifelse(dog == 1, "Dog", "Cat")) %>%
  mutate(returned = ifelse(outcome_type == "RETURNED TO OWNER", 1, 0)) %>%
  group_by(Species) %>%
  summarise(count = n(),
            meanDays = mean(shelter_days, na.rm = TRUE),
            `Proportion Euthanized` = sum(euthanized)/count,
            `Proportion Adopted` = sum(adopted)/count,
            `Proportion Stray` = sum(stray)/count,
           `Proportion Returned` = sum(returned)/count,
```

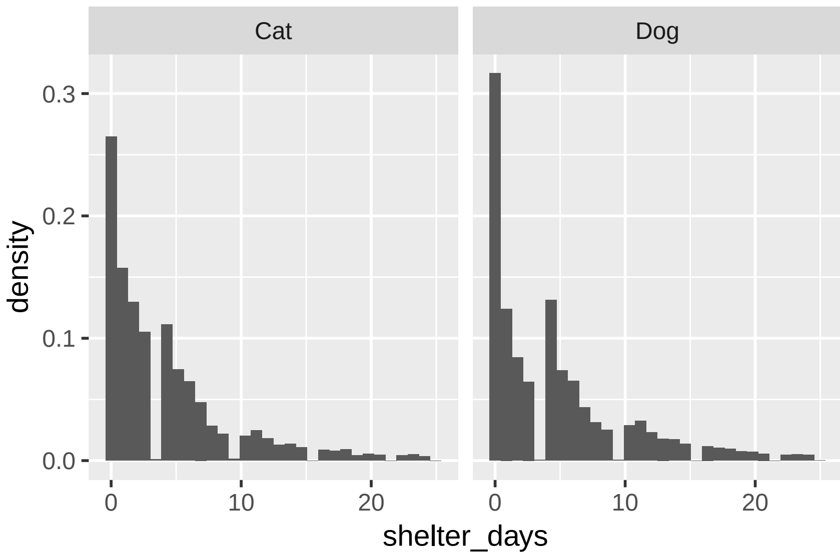
```r
          `Proportion Chipped` = sum(chip_status == "SCAN CHIP", na.rm = TRUE)/count)%>%
  gather(key = key, value = proportion, 4:8) %>%
  ggplot(aes(x=Species, y= proportion)) +
    geom_bar(stat = "identity")+
    facet_grid(cols = vars(key))
```



Cats are returned at a much lower rate than dogs. Cats have a much lower proportion with scannable chips than dogs.

```r
adoptions %>%
  filter(dog == 1 | cat == 1) %>%
  filter(shelter_days < 25) %>%
  mutate(DogCat = ifelse(dog == 1, "Dog", "Cat")) %>%
  ggplot(aes(x=shelter_days, y=..density..)) +
  geom_histogram()+
  facet_grid(~DogCat)
```

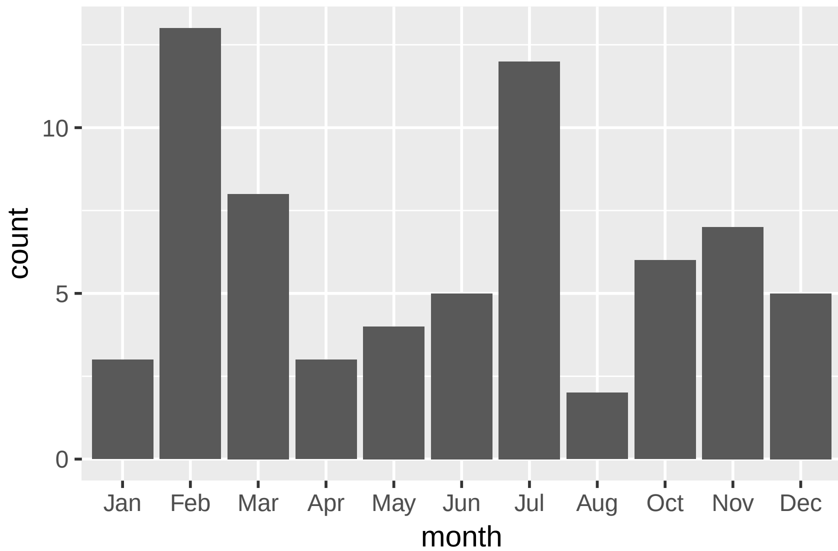
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



Dogs and cats show similar trends in the number of days until adoptions.

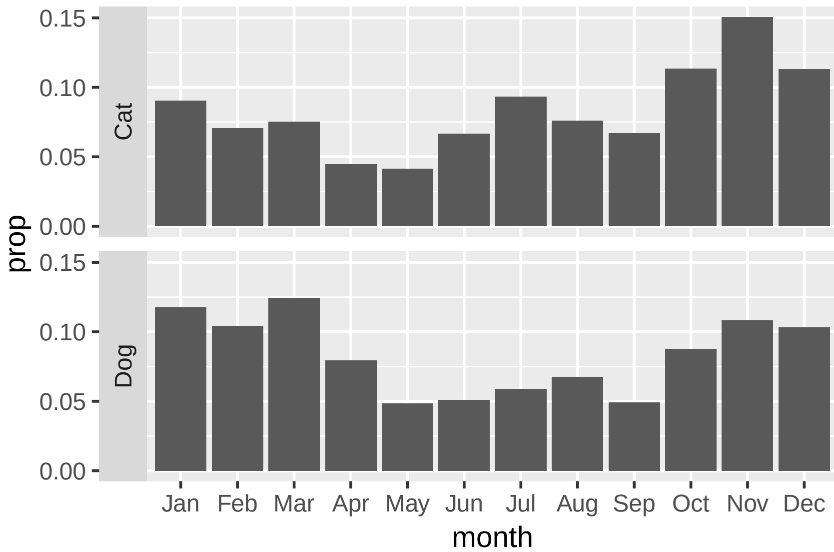
What about rabbits?

```
adoptions  %>%
  filter(animal_breed== "RABBIT SH") %>%
  filter(adopted == 1) %>%
  mutate(month = lubridate::month(outcome_date, label = TRUE)) %>%
  ggplot(aes(x=month)) +
  geom_bar()
```



Alright, so maybe it is not the case that more rabits are adopted over easter. Are there trends in dog adoptions?

```
adoptions  %>%
  filter(dog == 1 | cat == 1) %>%
  mutate(DogCat = ifelse(dog == 1, "Dog", "Cat")) %>%
  filter(adopted == 1, !is.na(month)) %>%
  mutate(month = lubridate::month(outcome_date, label = TRUE)) %>%
  ggplot(aes(x=month, y = ..prop.., group = 1)) +
  geom_bar()+
  facet_grid(rows = vars(DogCat), switch = "both")
```



These both seem to follow the trend of fewer adoptions in the summer.

Intake Condition

We are doing a preliminar investigation into this. There is no domunetation on what exactly all the different levels mean. For example we do not know what the difference between a manageable animal and a treatable animal are or what the differnce between a normal and a healthy animal are.

```
adoptions_expanded_intake=adoptions%>%
  mutate(healthy_intake=ifelse(grepl("^HEALTHY.*",intake_condition),1,0),
         contagious_intake=ifelse(grepl(".*[^NON-]CONTAGIOUS", intake_condition),1,0),
         untreatable_intake=ifelse(grepl(".*(UNTREATABLE).*", intake_condition),1,0),
         treatable_intake=ifelse(grepl("^TREATABLE.*", intake_condition),1,0),
         manageable_intake=ifelse(grepl(".*MANAGEABLE.*", intake_condition),1,0),
         rehabitable_intake=ifelse(grepl(".*REHABILITABLE.*", intake_condition),1,0),
         normal_intake=ifelse(grepl(".*NORMAL.*", intake_condition),1,0))
```

Healthy

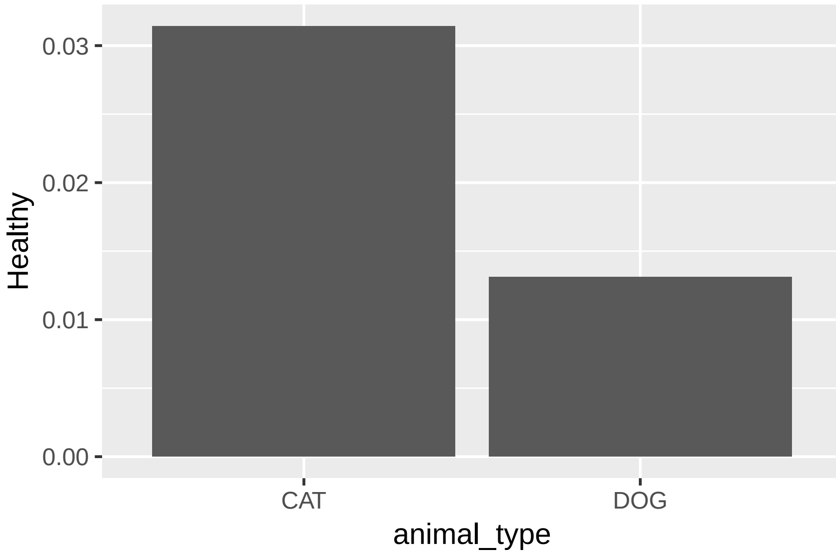
It looks like a slightly higher proportion of cats are healthy (0.0314) than dogs (0.0131), however both of there are suprisingly low.

```
adoptions_expanded_intake%>%
  filter(cat==1|dog==1)%>%
  group_by(animal_type)%>%
  summarise(Healthy=mean(healthy_intake))
```

```
## # A tibble: 2 x 2
##   animal_type Healthy
##   <chr>         <dbl>
## 1 CAT          0.0314
## 2 DOG          0.0131
```

```
adoptions_expanded_intake%>%
  filter(cat==1|dog==1)%>%
  group_by(animal_type)%>%
  summarise(Healthy=mean(healthy_intake))%>%
```

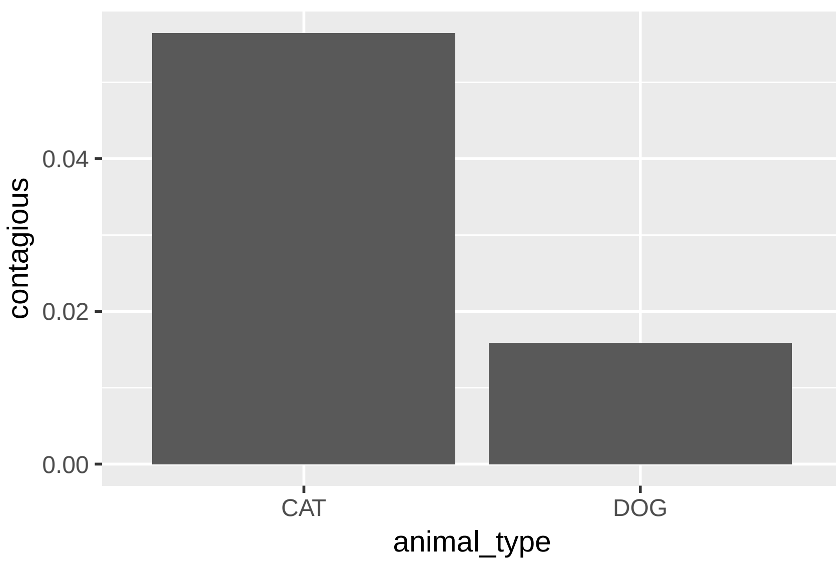
```
  ggplot(aes(x=animal_type, y=Healthy))+
  geom_bar(stat="identity")
```



Contagious

Even though a larger proportion of cats are found or given up healthy, a larger proportion of cats are contagious on intage (cats 0.0565 and dogs 0.0159).

```
adoptions_expanded_intake%>%
  filter(cat==1|dog==1)%>%
  group_by(animal_type)%>%
  summarise(contagious=mean(contagious_intake))%>%
  ggplot(aes(x=animal_type, y=contagious))+
  geom_bar(stat="identity")
```




```
adoptions_expanded_intake%>%
  filter(cat==1|dog==1)%>%
  group_by(animal_type)%>%
```

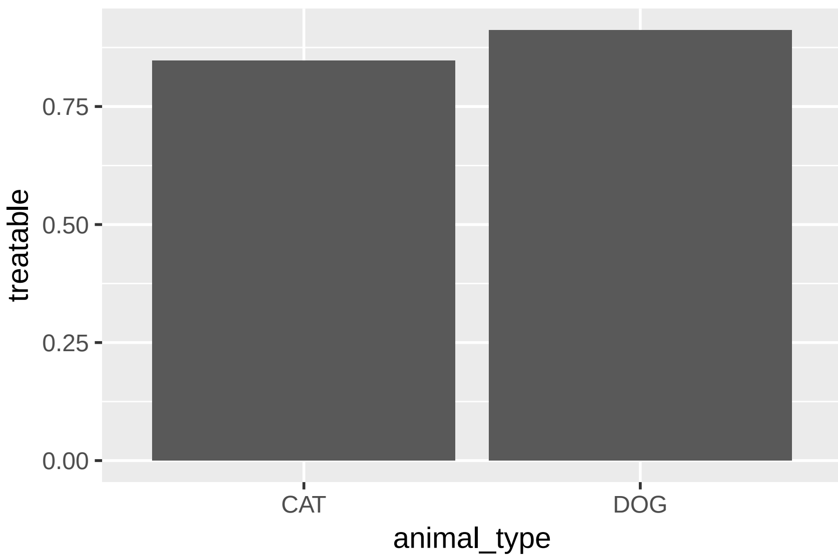
```
  summarise(contagious=mean(contagious_intake))
```

```
## # A tibble: 2 x 2
##   animal_type contagious
##   <chr>            <dbl>
## 1 CAT             0.0565
## 2 DOG             0.0159
```

Treatable

It looks like there is little difference in the proportion of cats and dogs that on intake are treatable.

```
adoptions_expanded_intake%>%
  filter(cat==1|dog==1)%>%
  group_by(animal_type)%>%
  summarise(treatable=mean(treatable_intake))%>%
  ggplot(aes(x=animal_type, y=treatable))+
  geom_bar(stat="identity")
```




```
adoptions_expanded_intake%>%
  filter(cat==1|dog==1)%>%
  group_by(animal_type)%>%
  summarise(treatable=mean(treatable_intake))
```

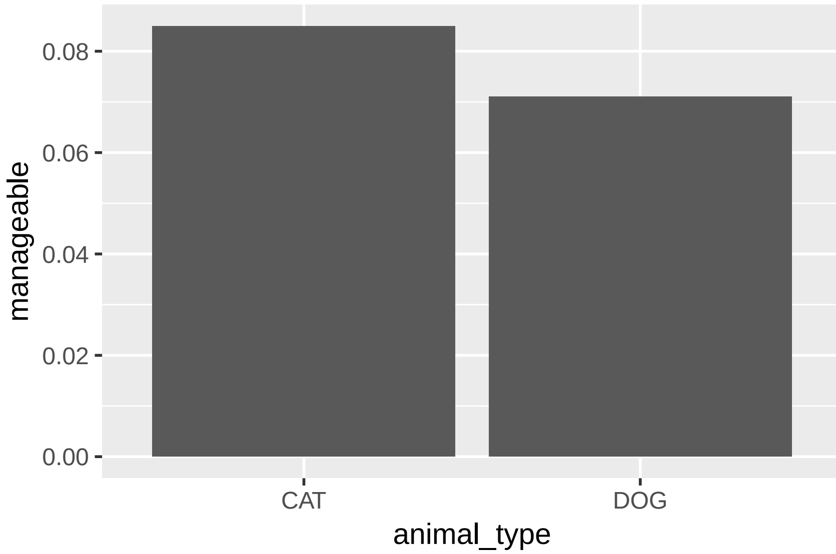
```
## # A tibble: 2 x 2
##   animal_type treatable
##   <chr>           <dbl>
## 1 CAT             0.847
## 2 DOG             0.912
```

Manageable

It appears that these are about the same for both cats and dogs

```
adoptions_expanded_intake%>%
  filter(cat==1|dog==1)%>%
  group_by(animal_type)%>%
  summarise(manageable=mean(manageable_intake))%>%
```

```r
  ggplot(aes(x=animal_type, y=manageable))+
  geom_bar(stat="identity")
```



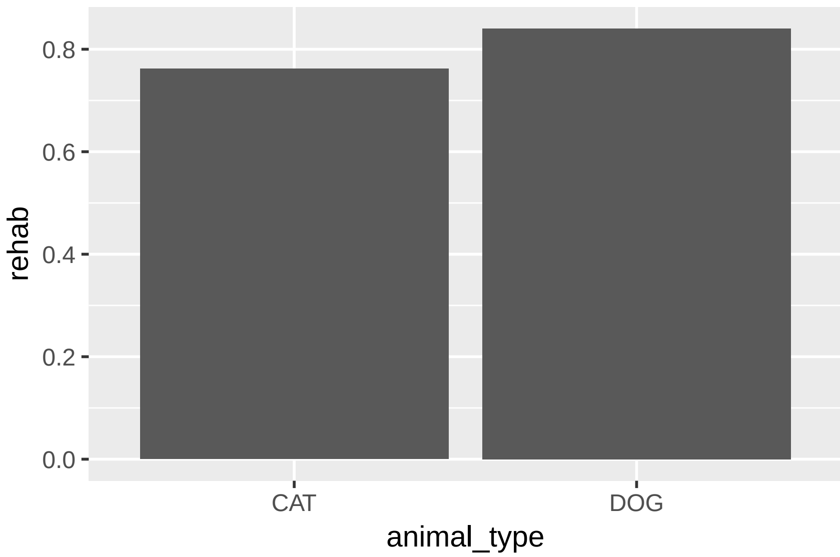

```r
adoptions_expanded_intake%>%
  filter(cat==1|dog==1)%>%
  group_by(animal_type)%>%
  summarise(manageable=mean(manageable_intake))
```

```
## # A tibble: 2 x 2
##   animal_type manageable
##   <chr>            <dbl>
## 1 CAT             0.0849
## 2 DOG             0.0711
```

Rehabilatable

It appears that these are about the same for both cats and dogs.

```r
adoptions_expanded_intake%>%
  filter(cat==1|dog==1)%>%
  group_by(animal_type)%>%
  summarise(rehab=mean(rehabitable_intake))%>%
  ggplot(aes(x=animal_type, y=rehab))+
  geom_bar(stat="identity")
```




```
adoptions_expanded_intake%>%
  filter(cat==1|dog==1)%>%
  group_by(animal_type)%>%
  summarise(rehabitable=mean(rehabitable_intake))
```

```
## # A tibble: 2 x 2
##   animal_type rehabitable
##   <chr>             <dbl>
## 1 CAT               0.762
## 2 DOG               0.841
```

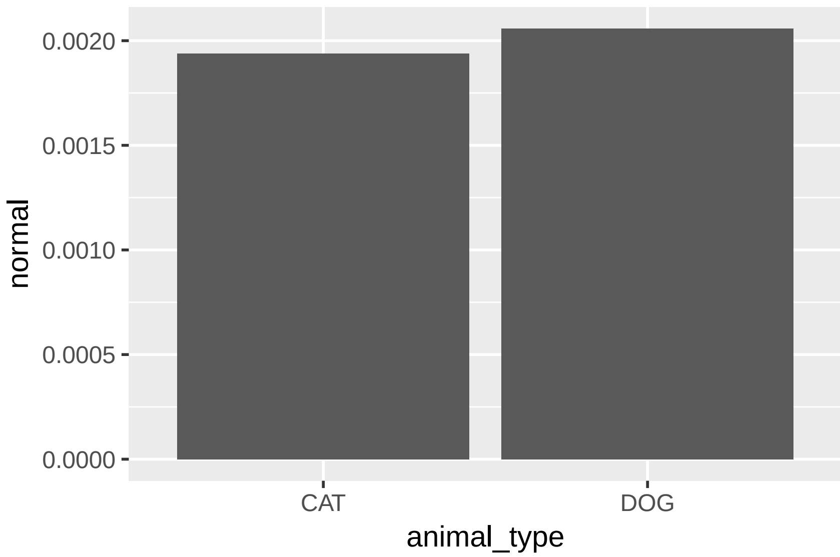
```
adoptions_expanded_intake%>%
  filter(animal_type=="CAT"|animal_type=="DOG")%>%
  filter(rehabitable_intake==1)%>%
  group_by(animal_type)%>%
  count()
```

```
## # A tibble: 2 x 2
## # Groups:   animal_type [2]
##   animal_type     n
##   <chr>       <int>
## 1 CAT          9822
## 2 DOG         37159
```

Normal

It looks like this was only used a few times and most likely is not important.

```
adoptions_expanded_intake%>%
  filter(cat==1|dog==1)%>%
  group_by(animal_type)%>%
  summarise(normal=mean(normal_intake))%>%
  ggplot(aes(x=animal_type, y=normal))+
  geom_bar(stat="identity")
```




```
adoptions_expanded_intake%>%
  filter(cat==1|dog==1)%>%
  group_by(animal_type)%>%
  summarise(normal=mean(normal_intake))
```

```
## # A tibble: 2 x 2
##   animal_type  normal
##   <chr>         <dbl>
## 1 CAT         0.00194
## 2 DOG         0.00206
```

Wildlife

```
adoptions%>%
  filter(animal_type=="WILDLIFE")%>%
  group_by(animal_breed)%>%
  count()
```

```
## # A tibble: 32 x 2
## # Groups:   animal_breed [32]
##    animal_breed     n
##    <chr>        <int>
##  1 ARMADILLO        2
##  2 BADGER           1
##  3 BAT             59
##  4 CALIFORNIAN      1
##  5 COTTONTAIL       2
##  6 COYOTE           4
##  7 DUTCH            1
##  8 FERRET           9
##  9 FOX             23
## 10 GERBIL           2
## # ... with 22 more rows
```

```
# Badger that was returned to owner
adoptions%>%
  filter(animal_breed=="BADGER")
```

```
## # A tibble: 1 x 23
##      X1 animal_breed animal_origin animal_type chip_status intake_condition
##   <dbl> <chr>        <chr>         <chr>       <chr>       <chr>
## 1 55453 BADGER       FIELD         WILDLIFE    SCAN NO CH~ TREATABLE REHAB~
## # ... with 17 more variables: intake_date <date>, intake_subtype <chr>,
## #   intake_type <chr>, outcome_condition <chr>, outcome_date <date>,
## #   outcome_type <chr>, year <dbl>, pitbull <dbl>, adopted <dbl>,
## #   euthanized <dbl>, surrendered <dbl>, stray <dbl>, dog <dbl>,
## #   cat <dbl>, shelter_days <dbl>, december <dbl>, month <dbl>
```

```
adoptions%>%
  filter(animal_breed=="CALIFORNIAN")
```

```
## # A tibble: 1 x 23
##      X1 animal_breed animal_origin animal_type chip_status intake_condition
##   <dbl> <chr>        <chr>         <chr>       <chr>       <chr>
## 1  4462 CALIFORNIAN  OVER THE COU~ WILDLIFE    SCAN NO CH~ TREATABLE REHAB~
## # ... with 17 more variables: intake_date <date>, intake_subtype <chr>,
## #   intake_type <chr>, outcome_condition <chr>, outcome_date <date>,
## #   outcome_type <chr>, year <dbl>, pitbull <dbl>, adopted <dbl>,
## #   euthanized <dbl>, surrendered <dbl>, stray <dbl>, dog <dbl>,
## #   cat <dbl>, shelter_days <dbl>, december <dbl>, month <dbl>
```

```
# Coyote that was handed over the counter (This means that someone dropeed of a coyote at the animal sh
adoptions%>%
  filter(animal_breed=="COYOTE",
         animal_origin=="OVER THE COUNTER")
```

```
## # A tibble: 1 x 23
##      X1 animal_breed animal_origin animal_type chip_status intake_condition
##   <dbl> <chr>        <chr>         <chr>       <chr>       <chr>
## 1 33871 COYOTE       OVER THE COU~ WILDLIFE    UNABLE TO ~ UNHEALTHY UNTRE~
## # ... with 17 more variables: intake_date <date>, intake_subtype <chr>,
## #   intake_type <chr>, outcome_condition <chr>, outcome_date <date>,
## #   outcome_type <chr>, year <dbl>, pitbull <dbl>, adopted <dbl>,
## #   euthanized <dbl>, surrendered <dbl>, stray <dbl>, dog <dbl>,
## #   cat <dbl>, shelter_days <dbl>, december <dbl>, month <dbl>
```

Livestock

```
adoptions%>%
  filter(animal_type=="LIVESTOCK")%>%
  group_by(animal_breed)
```

```
## # A tibble: 33 x 23
## # Groups:   animal_breed [6]
##       X1 animal_breed animal_origin animal_type chip_status
##    <dbl> <chr>        <chr>         <chr>       <chr>
##  1   938 ANGUS        FIELD         LIVESTOCK   SCAN NO CH~
##  2  2575 GOAT         OVER THE COU~ LIVESTOCK   UNABLE TO ~
##  3  2598 PIG          FIELD         LIVESTOCK   SCAN NO CH~
##  4  3090 PIG          FIELD         LIVESTOCK   SCAN NO CH~
##  5  5867 HORSE        FIELD         LIVESTOCK   SCAN NO CH~
##  6  8969 HORSE        FIELD         LIVESTOCK   SCAN NO CH~
##  7  9673 PIG          FIELD         LIVESTOCK   SCAN NO CH~
```

```
##  8 10218 PIG          FIELD         LIVESTOCK   UNABLE TO ~
##  9 10461 GOAT         FIELD         LIVESTOCK   UNABLE TO ~
## 10 11931 SHEEP        FIELD         LIVESTOCK   SCAN NO CH~
## # ... with 23 more rows, and 18 more variables: intake_condition <chr>,
## #   intake_date <date>, intake_subtype <chr>, intake_type <chr>,
## #   outcome_condition <chr>, outcome_date <date>, outcome_type <chr>,
## #   year <dbl>, pitbull <dbl>, adopted <dbl>, euthanized <dbl>,
## #   surrendered <dbl>, stray <dbl>, dog <dbl>, cat <dbl>,
## #   shelter_days <dbl>, december <dbl>, month <dbl>
```