Predicting Health Insurance Charge with tidymodels

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Medical Cost Personal Datasets

Insurance Forecast by using Linear Regression

Link to Kaggle Page

Link to GitHub Source

A little over a month ago, around the end of October, I attended the Open Data Science Conference primarily for the workshops and training sessions that were offered. The first workshop I attended was a demonstration by Jared Lander on how to implement machine learning methods in R using a new package named *tidymodels*. I went into that training knowing almost nothing about machine learning, and have since then drawn exclusively from free online materials to understand how to analyze data using this "meta-package."

As a brief introduction, tidymodels is, like tidyverse, not a single package but rather a collection of data science packages designed according to tidyverse principles. Many of the packages present in tidymodels are also present in tidyverse. What makes tidymodels different from tidyverse, however, is that many of these packages are meant for predictive modeling and provide a universal standard interface for all of the different machine learning methods available in R.

Today, we are using a data set of health insurance information from ~1300 customers of a health insurance company. This data set is sourced from a book titled *Machine Learning with R* by Brett Lantz.

```
library(tidyverse)
library(tidymodels)
library(data.table)

download.file("https://raw.githubusercontent.com/stedy/Machine-Learning-with-R-datasets/master/insuranc
              "insurance.csv")

insur_dt <- fread("insurance.csv")
```

```
insur_dt %>% colnames()
```

```
## [1] "age"      "sex"      "bmi"      "children" "smoker"   "region"   "charges"
```

```
insur_dt$age %>% summary()
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   18.00   27.00   39.00   39.21   51.00   64.00
```

```r
insur_dt$sex %>% table()
```

```
## .
## female   male
##    662    676
```

```r
insur_dt$bmi %>% summary()
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   15.96   26.30   30.40   30.66   34.69   53.13
```

```r
insur_dt$smoker %>% table()
```

```
## .
##   no  yes
## 1064  274
```

```r
insur_dt$charges %>% summary()
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1122    4740    9382   13270   16640   63770
```

Above, you'll noticed I loaded packages such as `parsnip` and `recipes`. These packages, together with others, form the meta-package `tidymodels` used for modeling and statistical analysis. You can learn more about it here. Usually, you can simply call `library(tidymodels)`, but Kaggle R notebooks seem unable to install and/or load it for the time being, which is fine.

As you can see, there are 7 different relatively self-explanatory variables in this data set, some of which are presumably used by the benevolent and ever-loving private health insurance company in question to determine how much a given individual is ultimately charged. `age`, `sex` and `region` appear to be demographics; with age going no lower than 18 and no greater than 64 with a mean of about 40. The two factor levels in `sex` seem to be about the same in quantity.

Assuming that the variable `bmi` corresponds to Body Mass Index, according to the CDC, a BMI of 30 or above is considered clinically obese. In our present data set, the average is just over the cusp of obese.

Next we have the number of smokers vs non-smokers. As someone who has filled out even one form before in my life, I can definitely tell you that `smoker` is going to be important going forward in determining the `charge` of each given heath insurance customer.

Lastly, we have `charge`. The average annual charge for health insurance is a modest $13,000.

```r
# 1, 2, 3, 4 etc. children as factor
insur_dt$children <- insur_dt$children %>% as.factor()

insur_dt
```

```
##       age    sex    bmi children smoker    region   charges
##    1:  19 female 27.900        0    yes southwest 16884.924
##    2:  18   male 33.770        1     no southeast  1725.552
##    3:  28   male 33.000        3     no southeast  4449.462
##    4:  33   male 22.705        0     no northwest 21984.471
##    5:  32   male 28.880        0     no northwest  3866.855
##   ---
## 1334:  50   male 30.970        3     no northwest 10600.548
## 1335:  18 female 31.920        0     no northeast  2205.981
## 1336:  18 female 36.850        0     no southeast  1629.833
## 1337:  21 female 25.800        0     no southwest  2007.945
## 1338:  61 female 29.070        0    yes northwest 29141.360
```

I want to first start off by saving the number of `children` as factor levels. This will help me with my analysis later on, since the number of children, in real life, are really a continuous variable (usually pretty limited, most people do not have more than a few at most).

Exploratory Data Analysis

```
skimr::skim(insur_dt)
```

Table 1: Data summary

Name	insur_dt
Number of rows	1338
Number of columns	7
Column type frequency:	
character	3
factor	1
numeric	3
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
sex	0	1	4	6	0	2	0
smoker	0	1	2	3	0	2	0
region	0	1	9	9	0	4	0

Variable type: factor

skim_variable	n_missing	complete_rate	ordered	n_unique	top_counts
children	0	1	FALSE	6	0: 574, 1: 324, 2: 240, 3: 157

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100
age	0	1	39.21	14.05	18.00	27.00	39.00	51.00	64.00
bmi	0	1	30.66	6.10	15.96	26.30	30.40	34.69	53.13
charges	0	1	13270.42	12110.01	1121.87	4740.29	9382.03	16639.91	63770.43

```
table(insur_dt$sex)
```

```
##
## female   male
##    662    676
```

I want to note that this data set is pretty clean; you will probably never encounter a data set like this in the wild. There are no `NA`s and, as I mentioned before, no class imbalance along `sex`. Let's look at the distribution of children:

```
table(insur_dt$children)
```

```
##
##   0   1   2   3   4   5
## 574 324 240 157  25  18
```

Pretty standard; the plurality of people in this set do not have children. The next highest amount is 1, the second highest 2, etc.

```
options(repr.plot.width=15, repr.plot.height = 10)

insur_dt %>%
    select(age, bmi, children, smoker, region, charges) %>%
    GGally::ggpairs(mapping = aes(color = region))
```

```
## Registered S3 method overwritten by 'GGally':
##   method from
##   +.gg   ggplot2
```

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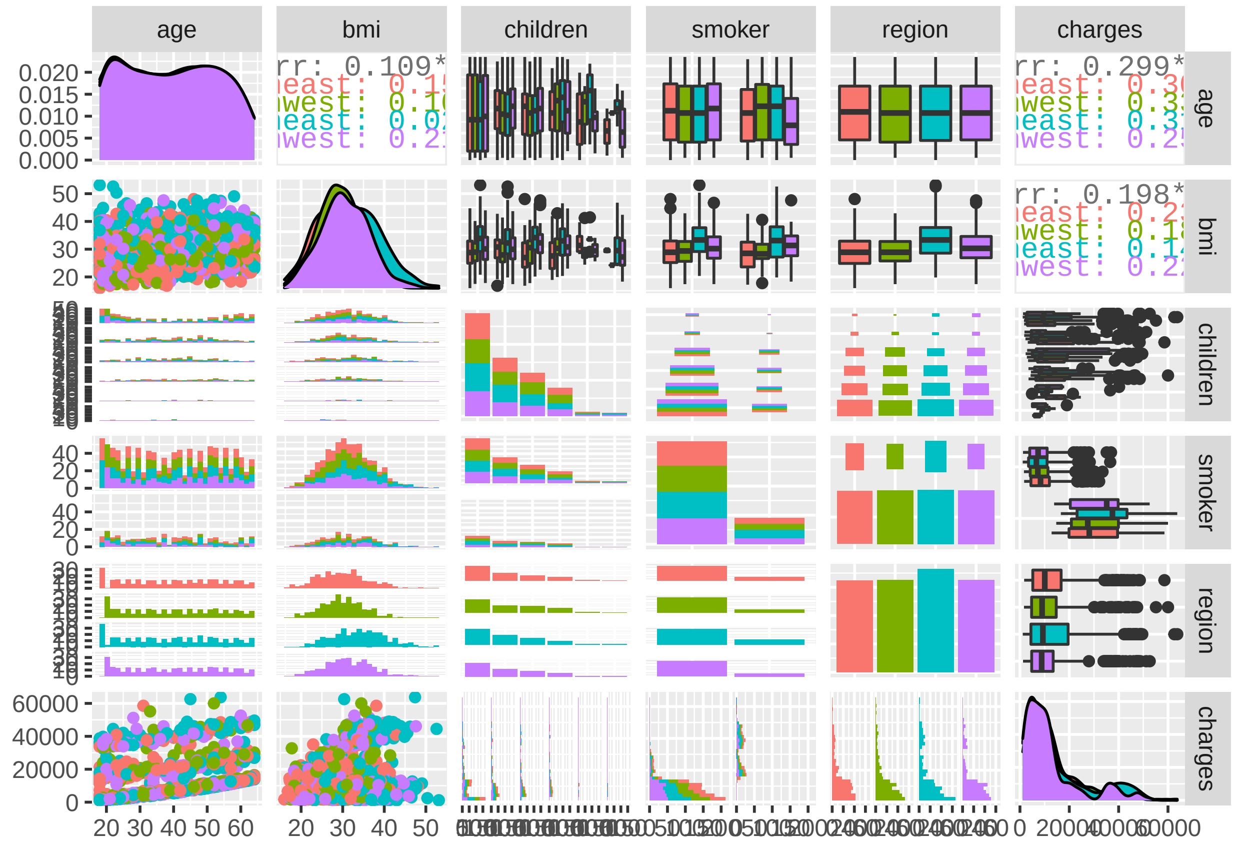
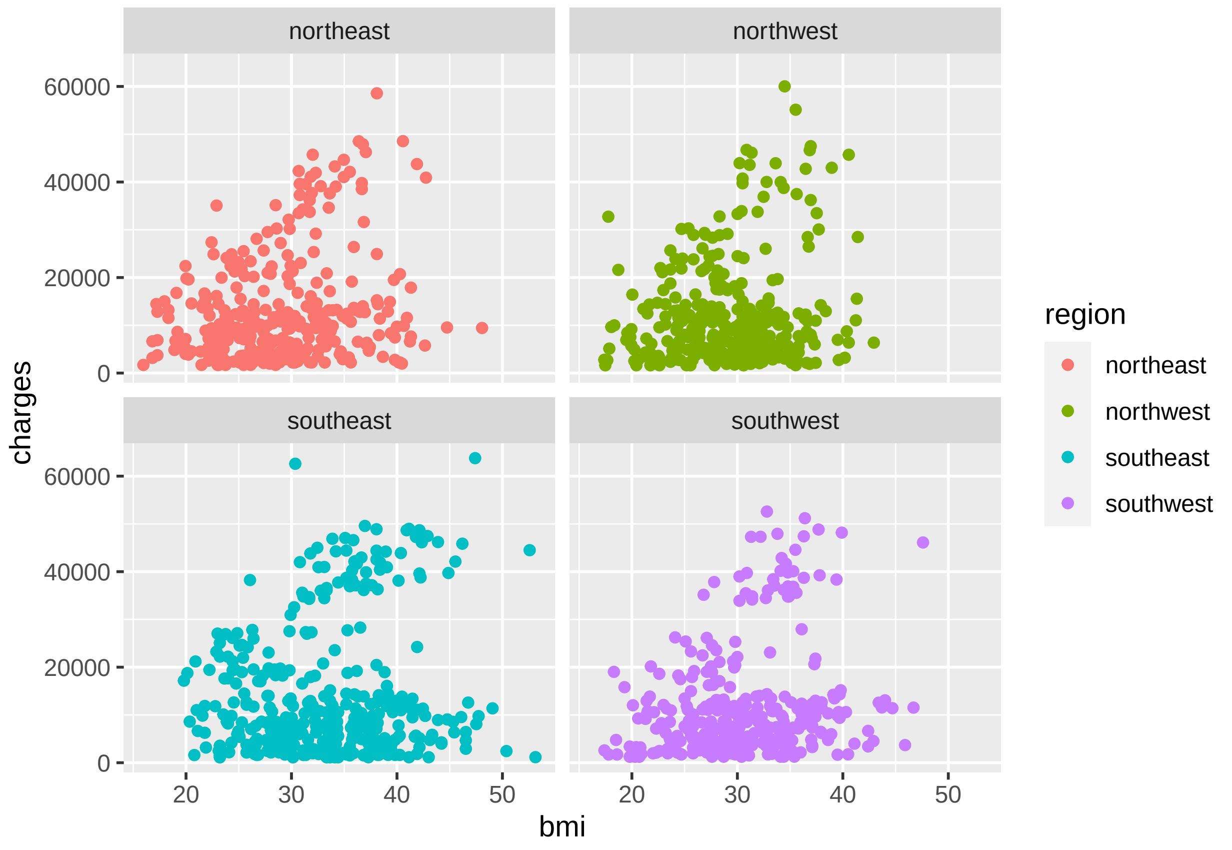



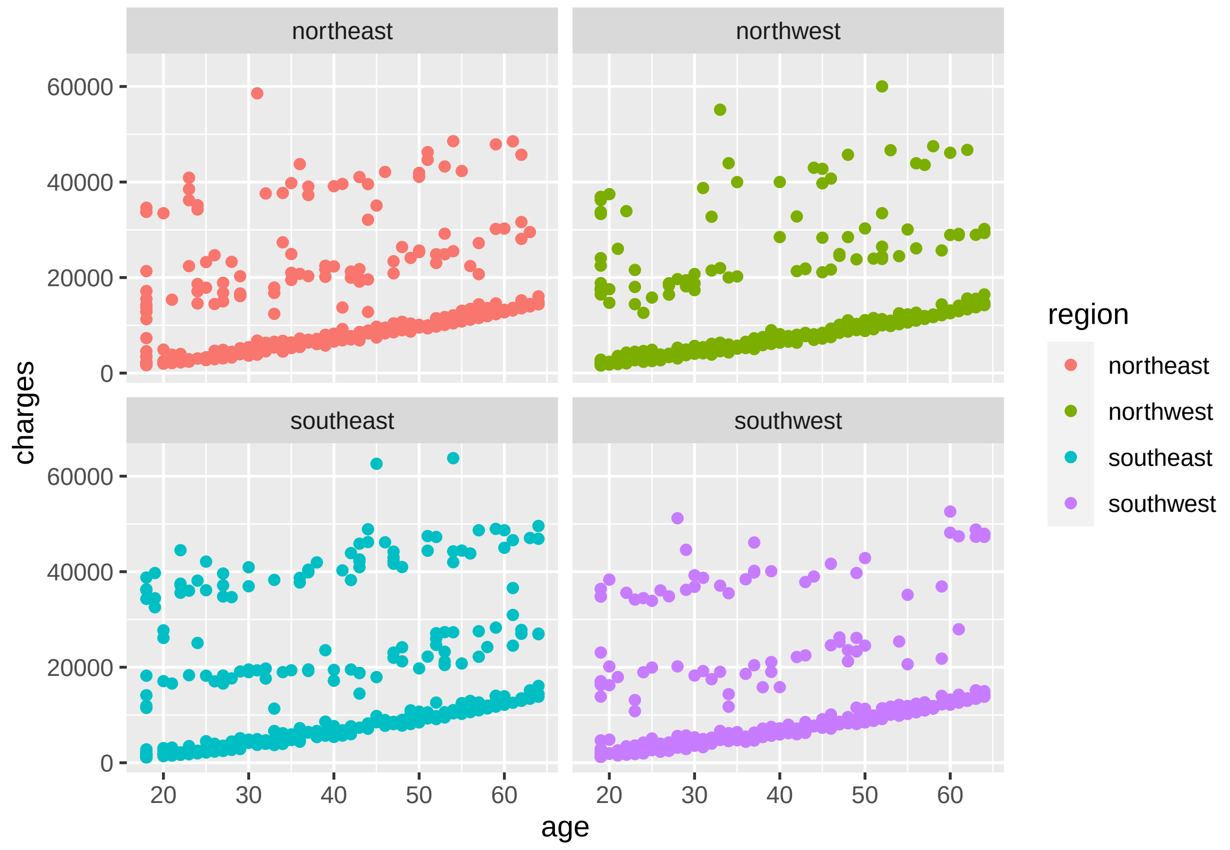
GGally is a package that I don't know too much about, but I do know that it contains a function called ggpairs, which sort of just generates a bunch of different plots with the variables you feed it and helps you get an overview of the relationships that exist betweeen them. Most of these plots are just noise, but there are a few interesting ones, such as the two on the bottom left assessing charge vs age and charge vs bmi. Further to the right, there is also charge vs smoker. Let's take a closer look at some of these relationships:

```
insur_dt %>% ggplot(aes(color = region)) + facet_wrap(~ region)+
  geom_point(mapping = aes(x = bmi, y = charges))
```



I wanted to see if there are regions that are somehow charged at a different rate than the others, but these plots all look basically the same. If you'll notice, there are about two different blobs projecting from 0,0 to the center of the plot. We'll get back to that later.

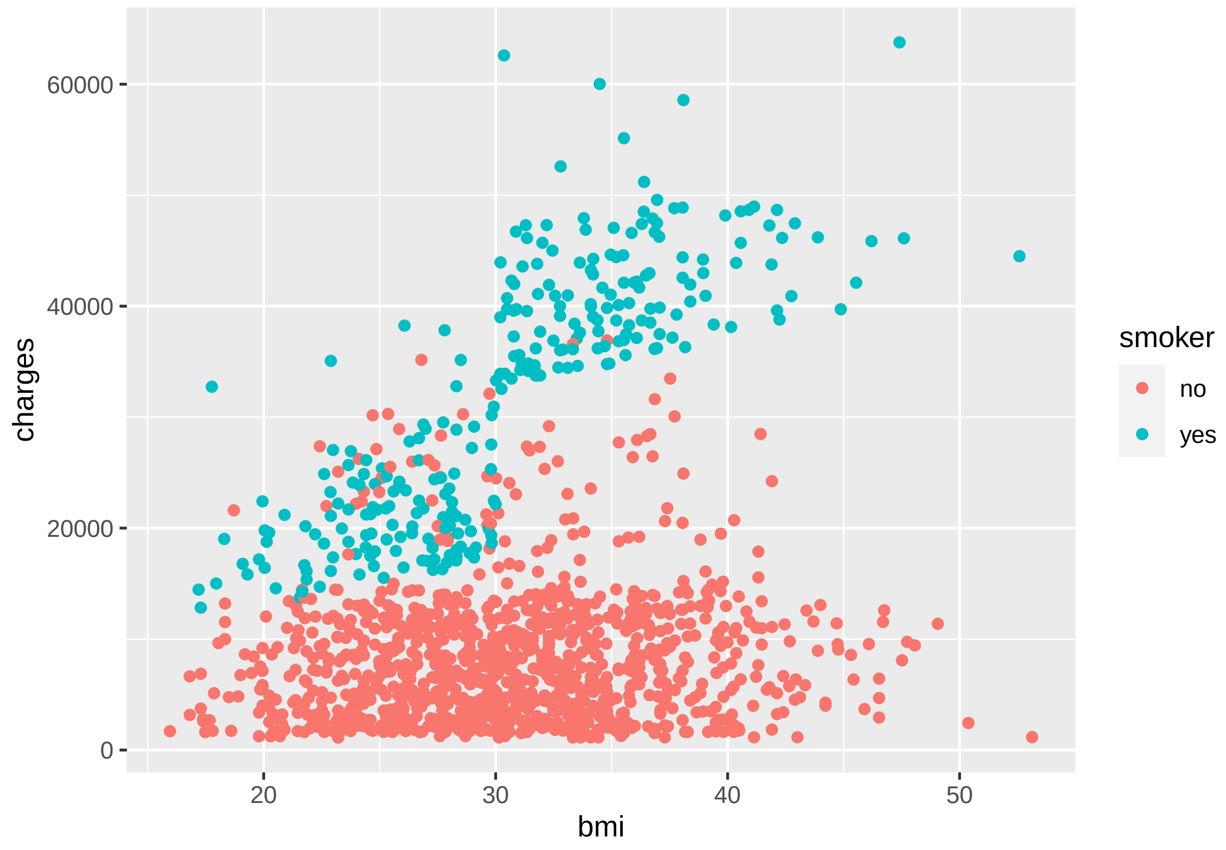
```
insur_dt %>% ggplot(aes(color = region)) + facet_wrap(~ region)+
  geom_point(mapping = aes(x = age, y = charges))
```



Here, I wanted to see if there was any sort of noticeable relationship between `age` and `charges`. Across the four `regions`, most tend to lie on a slope near the X-axis increasing modestly with `age`. There are, however, a pattern that appears to be two levels coming off of that baseline. Since we don't have a variable for the type of health insurance plan these people are using, we should probably hold off on any judgements on what this could be for now.

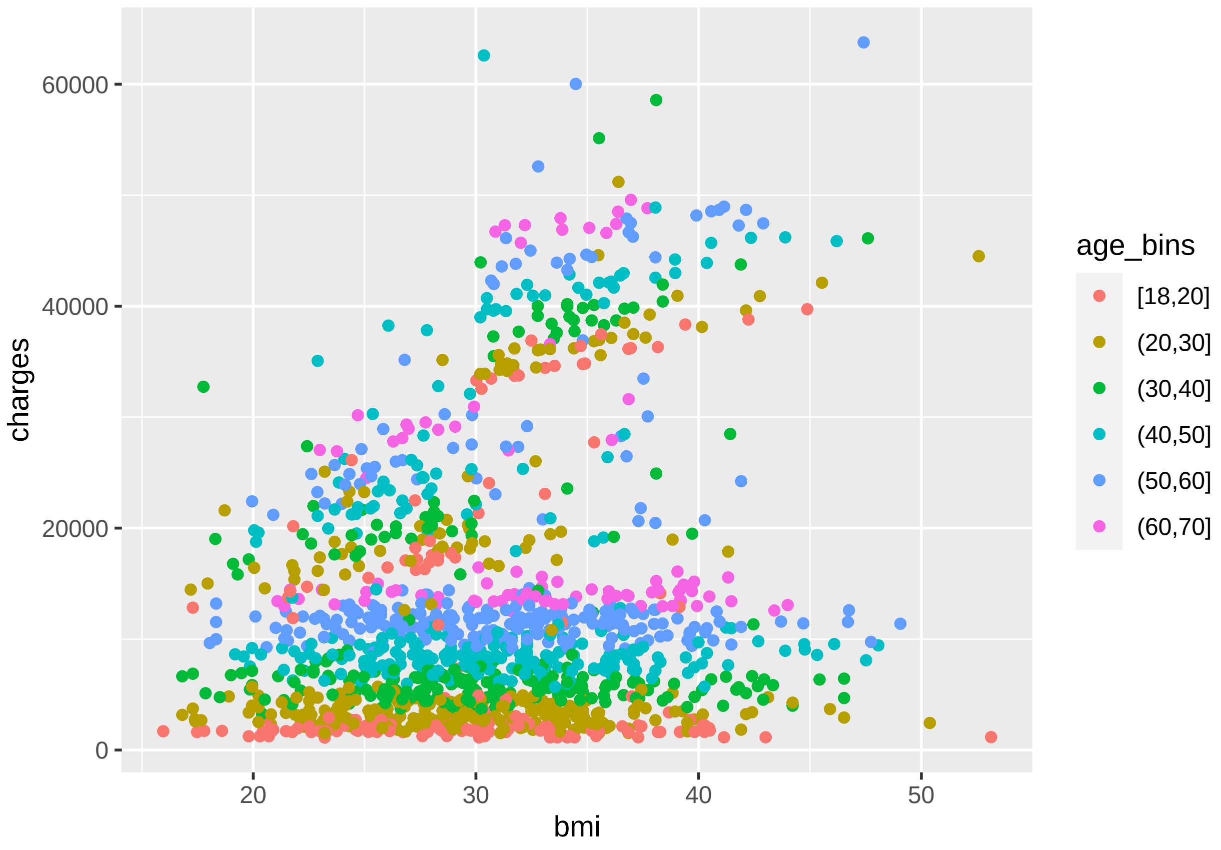
Let's move onto what is undoubtedly the pièce de résistance of health insurance coverage: smokers.

```
insur_dt %>%
    select(smoker, bmi, charges) %>%
    ggplot(aes(color = smoker)) +
    geom_point(mapping = aes(x = bmi, y = charges))
```



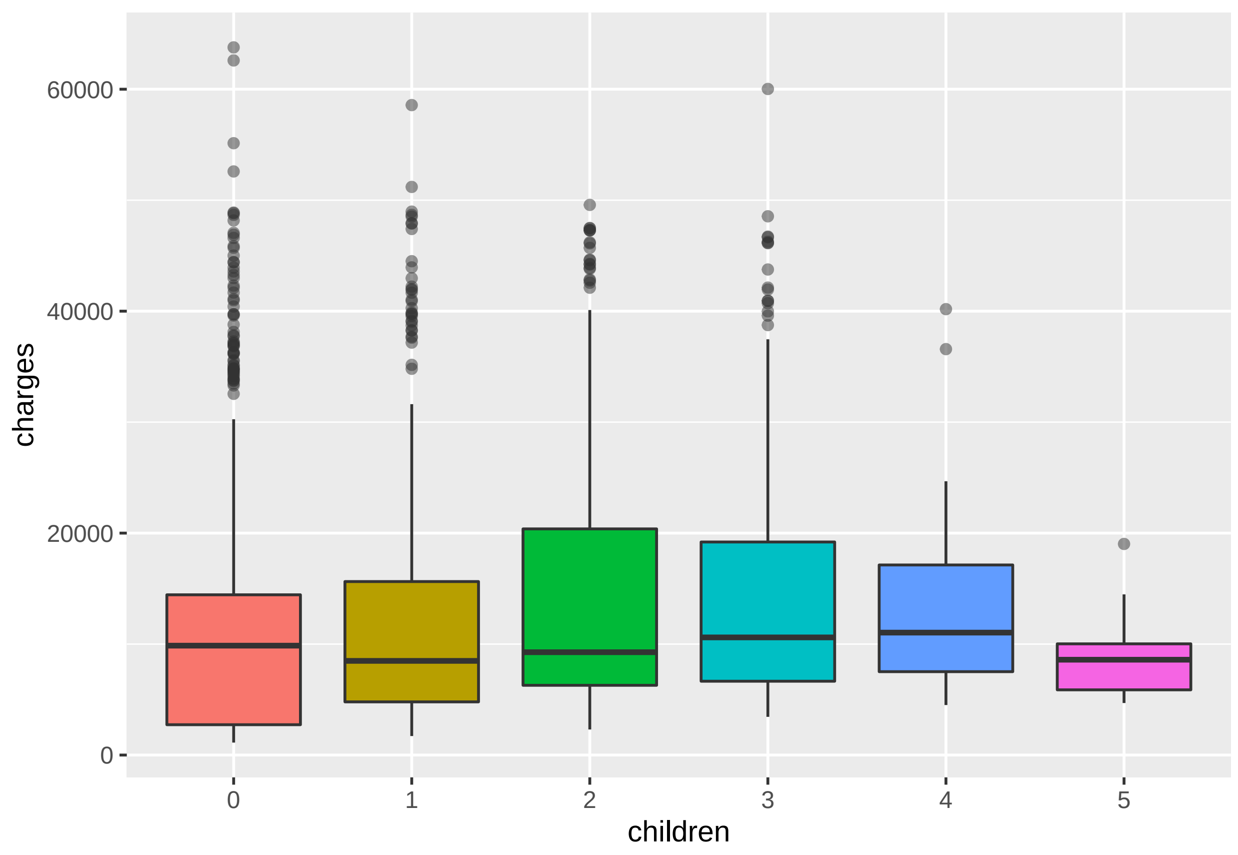
Wow. What a stark difference. Here, you can see that `smoker` almost creates a whole new blob of points separate from non-smokers... and that blob sharply rises after `bmi = 30`. Say, what was the CDC official cutoff for obesity again?

```
insur_dt$age_bins <- cut(insur_dt$age,
                breaks = c(18,20,30,40,50,60,70,80,90),
                include.lowest = TRUE,
                right = TRUE)

insur_dt %>%
    select(bmi, charges, sex, age_bins) %>%
    ggplot(aes(color = age_bins)) +
    geom_point(mapping = aes(x = bmi, y = charges))
```



You can see that `age` does play a role in `charge`, but it's still stratified within the 3-ish clusters of points, so even among the high-`bmi` smokers, younger people still pay less money than older people in a consistent way, so it makes sense. However, it does not appear that age interacts with `bmi` or `smoker`, meaning that it independently effects the `charge`.

```
insur_dt %>%
    select(children, charges, sex) %>%
    ggplot(aes(x = children, y = charges, group = children)) +
    geom_boxplot(outlier.alpha = 0.5, aes(fill = children)) +
    theme(legend.position = "none")
```



Finally, `children` does not affect `charge` significantly.

I think we've done enough exploratory analysis to establish that `bmi` and `smoker` together form a synergistic effect on `charge`, and that `age` also influences `charge` as well.

Build Model

```
set.seed(123)

insur_split <- initial_split(insur_dt, strata = smoker)

insur_train <- training(insur_split)
insur_test <- testing(insur_split)

# we are going to do data processing and feature engineering with recipes

# below, we are going to predict charges using everything else(".")
insur_rec <- recipe(charges ~ bmi + age + smoker, data = insur_train) %>%
    step_dummy(all_nominal()) %>%
    step_normalize(all_numeric(), -all_outcomes()) %>%
    step_interact(terms = ~ bmi:smoker_yes)

test_proc <- insur_rec %>% prep() %>% bake(new_data = insur_test)
```

```
## Warning: partial match of 'object' to 'objects'

## Warning: partial match of 'object' to 'objects'
## Warning: partial match of 'object' to 'objects'

## Warning: partial match of 'object' to 'objects'
```

We first split our data into training and testing sets. We stratify sampling by `smoker` status because there is an imbalance there and we want them to be equally represented in both the training and testing data sets. This is accomplished by first conducting random sampling within these classes.

An explanation of the `recipe`:

1. We are going to model the effect of `bmi`, `age` and `smoker` on `charges`. We do not specify interactions in this step because `recipe` handles interactions as a step.
2. We create dummy variables (`step_dummy`) for all nominal predictors, so `smoker` becomes `smoker_yes` and `smoker_no` is "implied" through omission (so if a row has `smoker_yes == 0`) because some models cannot have all dummy variables present as columns. To include all dummy variables, you can use `one_hot = TRUE`.
3. We then normalize all numeric predictors **except** our outcome variable(`step_normalize(all_numeric(), -all_outcomes())`), because you generally want to avoid transformations on outcomes when training and developing a model lest another data set inconsistent with the one you're using comes along and breaks your model. It's best do do transformations on outcomes before creating a `recipe`.
4. We are setting an interaction term; `bmi` and `smoker_yes` (the dummy variable for `smoker`), all interact with each other when effecting the outcome. Earlier, we noticed that older patients are charged more, and that older patients with higher `bmi` are charged even more than that. Well, older patients with a higher `bmi` who smoke are charged the most out of anyone in our data set. We observed this visually when looking at the plot, so we are going to also test this in the model we will develop.

Let's actually specify the model. We are going to be working with a k-Nearest Neighbors model, just for fun. The KNN model is simply defined as follows (according to some R markdown book I found online after Googling `knn simplified`):

> KNN regression is a non-parametric method that, in an intuitive manner, approximates the association between independent variables and the continuous outcome by averaging the observations in the same neighbourhood. The size of the neighbourhood needs to be set by the analyst or can be chosen using cross-validation (we will see this later) to select the size that minimises the mean-squared error.

To keep things simple, we are not going to use cross-validation to find the optimal `k`. Instead, we are just going to say `k = 10`. Another website I found said it's a good rule-of-thumb to keep `k = sqrt(n)`. I'm not going to do that because `nrow(insur_dt)    37`, although I suppose Kaggle's compute server's could handle it, so I don't see why not.

```r
knn_spec <- nearest_neighbor(neighbors = 10) %>%
    set_engine("kknn") %>%
    set_mode("regression")

knn_fit <- knn_spec %>%
    fit(charges ~ age + bmi + smoker_yes + bmi_x_smoker_yes,
        data = juice(insur_rec %>% prep()))
```

```
## Warning: partial match of 'object' to 'objects'

## Warning: partial match of 'object' to 'objects'
```

```r
insur_wf <- workflow() %>%
    add_recipe(insur_rec) %>%
    add_model(knn_spec)
```

We specified the model `knn_spec` by calling the model itself from `parsnip`, then we `set_engine` and set the mode to regression. Note the `neighbors` parameter in `nearest_neighbor`. That corresponds to the `k` in `knn`.

We then fit the model using the model specification to our data. Because we already computed columns for the `bmi` and `smoker_yes` interaction, we do not need to represent the interaction formulaically again.

Let's evaluate this model to see if it does good or does bad.

```
insur_cv <- vfold_cv(insur_train, prop = 0.9)

insur_rsmpl <- fit_resamples(insur_wf,
                           insur_cv,
                           control = control_resamples(save_pred = TRUE))
```

```
##
## Attaching package: 'rlang'

## The following object is masked from 'package:data.table':
##
##     :=

## The following objects are masked from 'package:purrr':
##
##     %@%, as_function, flatten, flatten_chr, flatten_dbl, flatten_int,
##     flatten_lgl, flatten_raw, invoke, list_along, modify, prepend,
##     splice

##
## Attaching package: 'vctrs'

## The following object is masked from 'package:dplyr':
##
##     data_frame

## The following object is masked from 'package:tibble':
##
##     data_frame

## ! Fold01: preprocessor 1/1: partial match of 'object' to 'objects'

## ! Fold01: preprocessor 1/1, model 1/1 (predictions): partial match of 'object' to ...

## ! Fold02: preprocessor 1/1: partial match of 'object' to 'objects'

## ! Fold02: preprocessor 1/1, model 1/1 (predictions): partial match of 'object' to ...

## ! Fold03: preprocessor 1/1: partial match of 'object' to 'objects'

## ! Fold03: preprocessor 1/1, model 1/1 (predictions): partial match of 'object' to ...

## ! Fold04: preprocessor 1/1: partial match of 'object' to 'objects'

## ! Fold04: preprocessor 1/1, model 1/1 (predictions): partial match of 'object' to ...

## ! Fold05: preprocessor 1/1: partial match of 'object' to 'objects'

## ! Fold05: preprocessor 1/1, model 1/1 (predictions): partial match of 'object' to ...

## ! Fold06: preprocessor 1/1: partial match of 'object' to 'objects'

## ! Fold06: preprocessor 1/1, model 1/1 (predictions): partial match of 'object' to ...
## ! Fold07: preprocessor 1/1: partial match of 'object' to 'objects'
## ! Fold07: preprocessor 1/1, model 1/1 (predictions): partial match of 'object' to ...
## ! Fold08: preprocessor 1/1: partial match of 'object' to 'objects'
## ! Fold08: preprocessor 1/1, model 1/1 (predictions): partial match of 'object' to ...
## ! Fold09: preprocessor 1/1: partial match of 'object' to 'objects'
## ! Fold09: preprocessor 1/1, model 1/1 (predictions): partial match of 'object' to ...
## ! Fold10: preprocessor 1/1: partial match of 'object' to 'objects'
## ! Fold10: preprocessor 1/1, model 1/1 (predictions): partial match of 'object' to ...
```

```
insur_rsmpl %>% collect_metrics()
```

```
## # A tibble: 2 x 6
##   .metric .estimator     mean     n  std_err .config
##   <chr>   <chr>         <dbl> <int>    <dbl> <chr>
## 1 rmse    standard   4916.       10 274.     Preprocessor1_Model1
## 2 rsq     standard      0.827    10   0.0194 Preprocessor1_Model1
```

```
summary(insur_dt$charges)
```

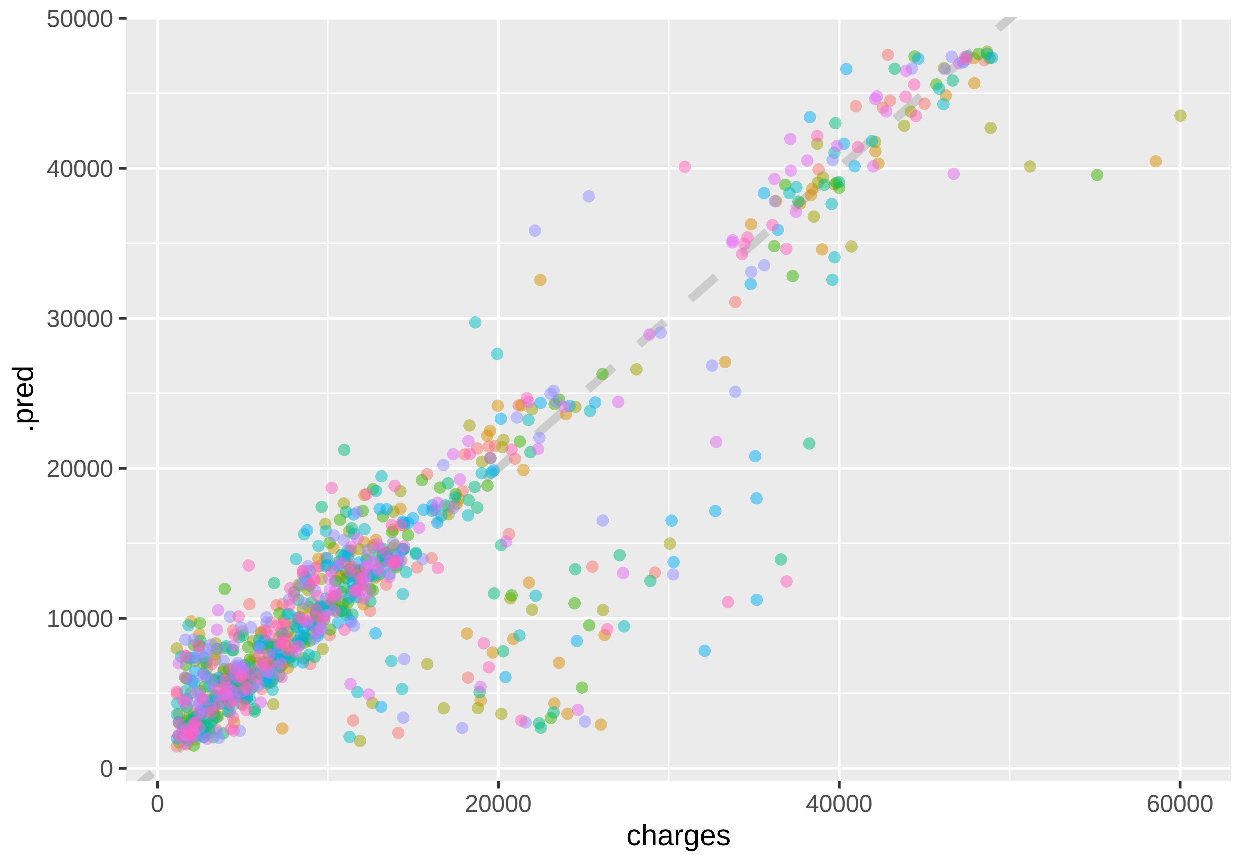
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1122    4740    9382   13270   16640   63770
```

We set `vfold_cv` (which is the cross validation that most people are familiar with, wherein the training data is split into V folds and then is trained on V-1 folds in order to make a prediction on the last fold, and is repeated so that all folds are trained and used as a prediction fold) to a `prop` of `0.9`, which is the same as specifying 9 training folds and 1 testing fold (within our training data).

We then finally run the cross validation by using `fit_resamples`. As you can see, we used our workflow object as our input.

Finally, we call `collect_metrics` to examine the model effectiveness. We end up with an `rmse` of 4,915 and an `rsq` of `0.82`. The RMSE would suggest that, on average, our predictions varied from observed values by an absolute measure of 4,915, in this case, dollars in `charges`. The R^2 would suggest that our regression has a fit of ~82%, although a high R^2 doesn't always mean the model has a good fit and a low R^2 doesn't always mean that a model has a poor fit, for reasons that are beyond me.

```
insur_rsmpl %>%
    unnest(.predictions) %>%
    ggplot(aes(charges, .pred, color = id)) +
    geom_abline(lty = 2, color = "gray80", size = 1.5) +
    geom_point(alpha = 0.5) +
    theme(legend.position = "none")
```



Above is a demonstration of our regression fit to a line. There is a large cluster of values that are model simply does not capture, and we could learn more about these points, but instead we are going to move on to applying our model to our test data, which we defined much earlier in this project.

```
insur_test_res <- predict(knn_fit, new_data = test_proc %>% select(-charges))
```

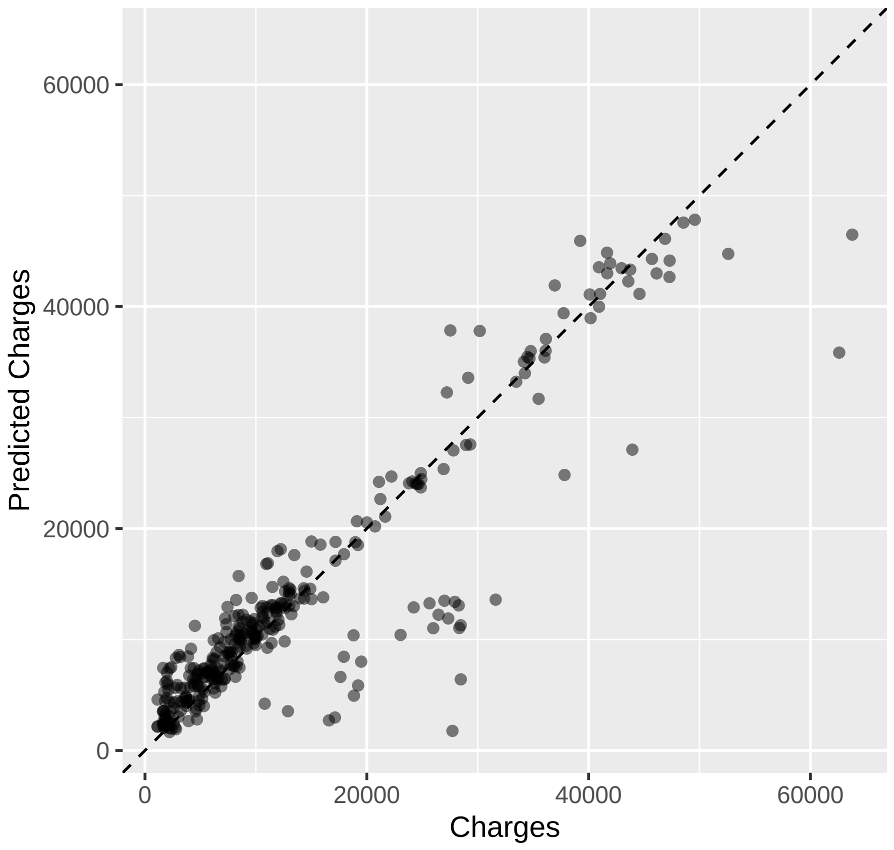
```
## Warning: partial match of 'fit' to 'fitted.values'
```

```
insur_test_res <- bind_cols(insur_test_res, insur_test %>% select(charges))

insur_test_res
```

```
## # A tibble: 334 x 2
##     .pred charges
##     <dbl>   <dbl>
##  1  4339.   3757.
##  2 27038.  27809.
##  3  2231.   1837.
##  4  6500.   6204.
##  5  2794.   4688.
##  6  6057.   6314.
##  7 14335.  12630.
##  8  1663.   2211.
##  9  5655.   3580.
## 10 39401.  37743.
## # ... with 324 more rows
```

We’ve now applied our model to `test_proc`, which is the test set after we’ve used the `recipes` preprocessing steps on them to transform them in the same way we transformed our training data. We bind the resulting predictions with the actual `charges` found in the training data to create a two-column table with our predictions and the corresponding real values we attempted to predict.

```
ggplot(insur_test_res, aes(x = charges, y = .pred)) +
  # Create a diagonal line:
  geom_abline(lty = 2) +
  geom_point(alpha = 0.5) +
  labs(y = "Predicted Charges", x = "Charges") +
  # Scale and size the x- and y-axis uniformly:
  coord_obs_pred()
```



```
rmse(insur_test_res, truth = charges, estimate = .pred)
```

```
## # A tibble: 1 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 rmse    standard       4985.
```

```
insur_rsmpl %>%
    collect_metrics()
```

```
## # A tibble: 2 x 6
##   .metric .estimator     mean     n  std_err .config
##   <chr>   <chr>         <dbl> <int>    <dbl> <chr>
## 1 rmse    standard   4916.       10 274.     Preprocessor1_Model1
## 2 rsq     standard      0.827    10   0.0194 Preprocessor1_Model1
```

Nice! The RMSE generated by our test data is insignificantly different from the one generated by our cross-validation! That means our model can reliably reproduce predictions with approximately the same level of error.

To be quite honest, now I want to configure a linear regression model the same way just to compare the results between the two. Fortunately, `tidymodels` makes this easy.

Linear Regression

We already have the recipe. All we need now is to specify a linear model and cross-validate the fit to test it on the testing data.

```
lm_spec <- linear_reg() %>%
    set_engine("lm")

lm_fit <- lm_spec %>%
    fit(charges ~ age + bmi + smoker_yes + bmi_x_smoker_yes,
        data = juice(insur_rec %>% prep()))
```

```
## Warning: partial match of 'object' to 'objects'

## Warning: partial match of 'object' to 'objects'
```

```
insur_lm_wf <- workflow() %>%
    add_recipe(insur_rec) %>%
    add_model(lm_spec)
```

We just repeat *some* of the same steps that we did for KNN but for the linear model. We can even cross-validate by using (almost) the same command:

```
insur_lm_rsmpl <- fit_resamples(insur_lm_wf,
                                insur_cv,
                                control = control_resamples(save_pred = TRUE))
```

```
## ! Fold01: preprocessor 1/1: partial match of 'object' to 'objects'

## ! Fold01: preprocessor 1/1, model 1/1 (predictions): partial match of 'object' to ...

## ! Fold02: preprocessor 1/1: partial match of 'object' to 'objects'

## ! Fold02: preprocessor 1/1, model 1/1 (predictions): partial match of 'object' to ...

## ! Fold03: preprocessor 1/1: partial match of 'object' to 'objects'

## ! Fold03: preprocessor 1/1, model 1/1 (predictions): partial match of 'object' to ...

## ! Fold04: preprocessor 1/1: partial match of 'object' to 'objects'

## ! Fold04: preprocessor 1/1, model 1/1 (predictions): partial match of 'object' to ...

## ! Fold05: preprocessor 1/1: partial match of 'object' to 'objects'

## ! Fold05: preprocessor 1/1, model 1/1 (predictions): partial match of 'object' to ...

## ! Fold06: preprocessor 1/1: partial match of 'object' to 'objects'

## ! Fold06: preprocessor 1/1, model 1/1 (predictions): partial match of 'object' to ...

## ! Fold07: preprocessor 1/1: partial match of 'object' to 'objects'

## ! Fold07: preprocessor 1/1, model 1/1 (predictions): partial match of 'object' to ...

## ! Fold08: preprocessor 1/1: partial match of 'object' to 'objects'
## ! Fold08: preprocessor 1/1, model 1/1 (predictions): partial match of 'object' to ...
## ! Fold09: preprocessor 1/1: partial match of 'object' to 'objects'
## ! Fold09: preprocessor 1/1, model 1/1 (predictions): partial match of 'object' to ...
## ! Fold10: preprocessor 1/1: partial match of 'object' to 'objects'
## ! Fold10: preprocessor 1/1, model 1/1 (predictions): partial match of 'object' to ...
```

```
insur_lm_rsmpl %>%
    collect_metrics()
```

```
## # A tibble: 2 x 6
##   .metric .estimator     mean     n  std_err .config
##   <chr>   <chr>         <dbl> <int>    <dbl> <chr>
## 1 rmse    standard   4866.       10 251.     Preprocessor1_Model1
## 2 rsq     standard      0.832    10   0.0162 Preprocessor1_Model1
```

```
insur_rsmpl %>%
    collect_metrics()
```

```
## # A tibble: 2 x 6
##   .metric .estimator     mean     n  std_err .config
##   <chr>   <chr>         <dbl> <int>    <dbl> <chr>
## 1 rmse    standard   4916.       10 274.     Preprocessor1_Model1
## 2 rsq     standard      0.827    10   0.0194 Preprocessor1_Model1
```

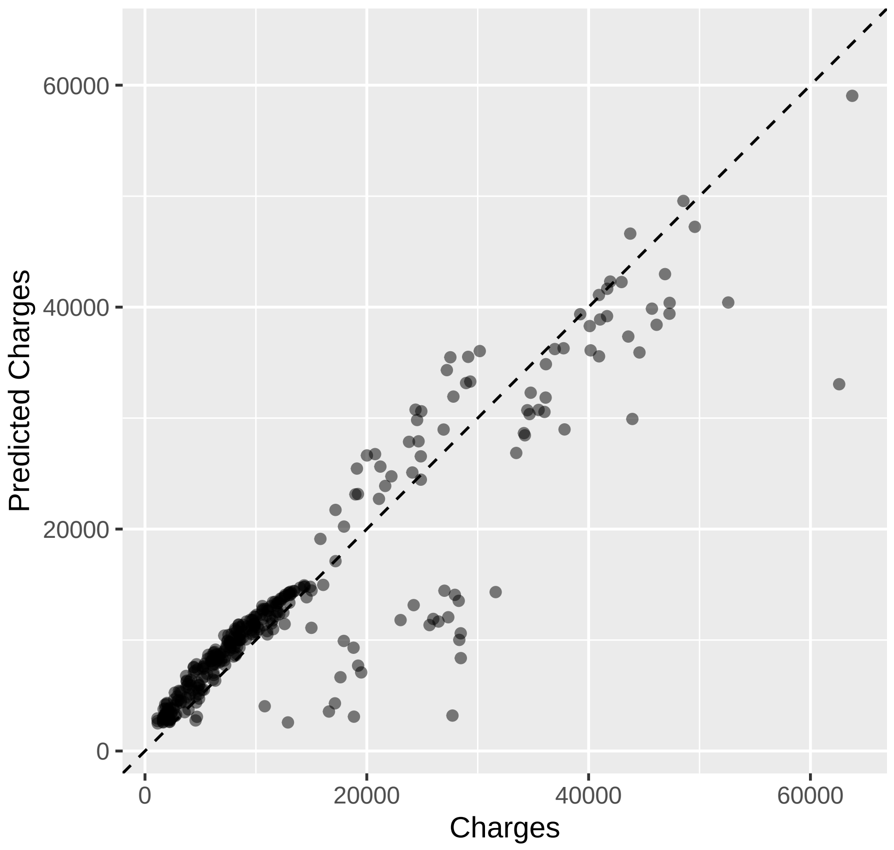
Fascinating! It appears that the good, ol' fashioned linear model beat k-Nearest Neighbors both in terms of RMSE but also R^2 across 10 cross-validation folds.

```
insur_test_lm_res <- predict(lm_fit, new_data = test_proc %>% select(-charges))

insur_test_lm_res <- bind_cols(insur_test_lm_res, insur_test %>% select(charges))

insur_test_lm_res
```

```
## # A tibble: 334 x 2
##     .pred charges
##     <dbl>   <dbl>
##  1  6335.   3757.
##  2 31938.  27809.
##  3  3171.   1837.
##  4  7878.   6204.
##  5  3081.   4688.
##  6  7815.   6314.
##  7 14070.  12630.
##  8  2656.   2211.
##  9  3498.   3580.
## 10 36293.  37743.
## # ... with 324 more rows
```

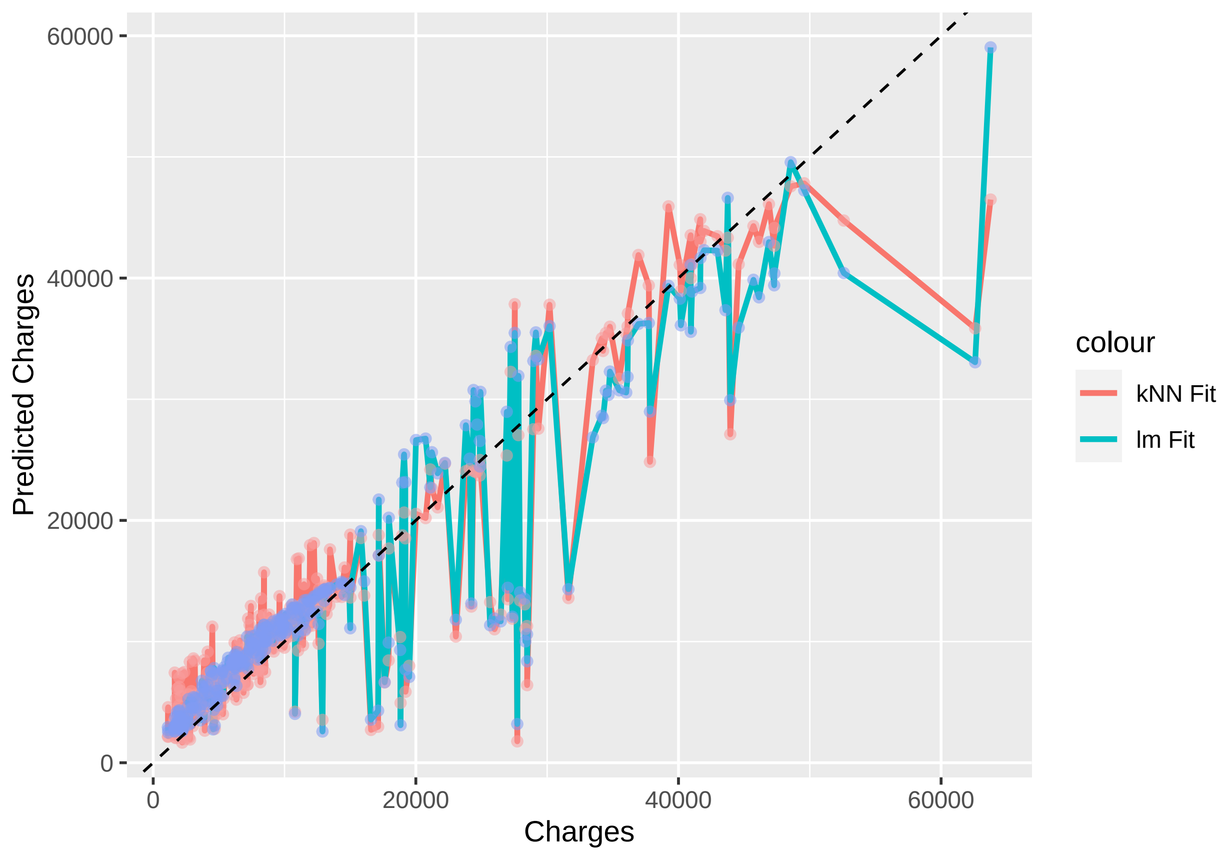
Now that we have our predictions, let's look at how well the linear model fared:

```
ggplot(insur_test_lm_res, aes(x = charges, y = .pred)) +
  # Create a diagonal line:
  geom_abline(lty = 2) +
  geom_point(alpha = 0.5) +
  labs(y = "Predicted Charges", x = "Charges") +
  # Scale and size the x- and y-axis uniformly:
  coord_obs_pred()
```



It seems as though the area on the bottom left corner had the greatest concentration of charges, and explains most of the `lm` fit. Look at both of these plots makes me wonder if there was a better model we could have used, but our model was sufficient given our purposes and level of accuracy.

```
combind_dt <- mutate(insur_test_lm_res,
      lm_pred = .pred,
      charges = charges
      ) %>% select(-.pred) %>%
    add_column(knn_pred = insur_test_res$.pred)

ggplot(combind_dt, aes(x = charges)) +
    geom_line(aes(y = knn_pred, color = "kNN Fit"), size = 1) +
    geom_line(aes(y = lm_pred, color = "lm Fit"), size = 1) +
    geom_point(aes(y = knn_pred, alpha = 0.5), color = "#F99E9E") +
    geom_point(aes(y = lm_pred, alpha = 0.5), color = "#809BF4") +
    geom_abline(size = 0.5, linetype = "dashed") +
    xlab('Charges') +
    ylab('Predicted Charges') +
    guides(alpha = FALSE)
```



Above is a comparison of the two methods with their respective predictions, and with the dotted line representing the "correct" values. In this case, the two models were not different enough from each other for their differences to be readily observed when plotted against each other, but there will be instances in the future wherein your two models do differ substantially, and this sort of plot will bolster your case for using one model over another.

Conclusion

Here, we were able to build a KNN model with our training data and use it to predict values in our testing data. To do this, we: * performed EDA * preprocessed our data using `recipes` * specified our model to be KNN * fit it to our training data * ran cross validation to produce accurate error statistics * predicted values in our test set * compared observed test set values with our predictions * specified another model, lm * performed a cross-validation * discovered lm to be the better model

I'm very excited to continue using tidymodels in R as a way to apply machine learning methods. If you're interested, I recommend checking out Tidy Modeling with R by Max Kuhn and Julia Silge.