Mushroom Edibility Analysis

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Introduction

Project Motivation / Background:

Mushrooms are vital to the general wellness of the ecosystem, decomposing and recycling the nutrients in the soil. Mushrooms also provide a valuable food source full of nutrients for human beings and other important organisms. However, some mushroom species can also be poisonous and harmful.

The importance of this research has been highlighted in a multitude of studies. Take this quote, for example:

> The ingestion of wild and potentially toxic mushrooms is common in the United States, with poison centers logging cases in the National Poison Data System (NPDS) for over 30 years. From 1999 to 2016, there were 133,700 reported cases of mushroom exposure, mostly unintentional and involving children under six years old. While the majority of cases resulted in no or minor harm, there were 704 instances of major harm and 52 fatalities, primarily due to cyclopeptide-producing mushrooms ingested unintentionally by older adults. Misidentification of edible mushroom species is a common cause of poisoning and may be preventable through education (Brandenburg and Ward 2018).

As shown by studies and other similar studies, accurate classification of mushrooms is crucial for preventing poisoning incidents. Many toxic mushroom species closely resemble edible varieties, making it easy for foragers to misidentify them. Thus, our research will focus on what physical features and environmental factors of mushrooms humans foragers can use to identify toxic/poisonous mushrooms in the wild. By conducting a research study on how to distinguish between safe and dangerous species, we can mitigate the incidence of mushroom poisoning and ensure safer foraging practices.

Research Question:

What environmental factors and/or physical features of mushrooms help indicate that a wild mushroom is poisonous or edible?

Hypothesis:

Mushrooms in the wild with obvious physical features like white gills, white rings, red caps, or red stems tend to be poisonous. These obvious physical traits are more likely to be spotted by animals, which would provide an evolutionary disadvantage unless they contain certain self-defense mechanisms, such as poison or toxins. Additionally, the habitat and season in which mushrooms are planted and grow may also affect whether they're poisonous. Different temperatures, humidity, and light can affect the production of toxins, which may also affect the edibility of mushrooms.

Data Description:

The data was curated on April 26, 1987, and submitted to the UCI by the National Audubon Society Field Guide. The National Audubon Society conducted extensive field research throughout North America, recording their observations on various aspects of mushrooms. Their research incorporate a wide range of physical characteristics, including size, shape, color, and texture of the mushrooms. Additionally, they documented environmental factors such as the type of habitat and seasonal variations. Importantly, the study also focused on the toxicity of the mushrooms, noting which species were poisonous. This comprehensive dataset provides valuable insights into the relationship between mushrooms and their environments, contributing significantly to the understanding of the factors influencing mushroom toxicity.

Our response variable is `class`, which is a qualitative variable labeled "e" for edible or "p" for poisonous.

Because we want our classifier to be easily used by people, and quantitative predictors can be harder to measure, we will focus on only one. That is `cap.diameter`, the diameter of the mushroom cap (cm).

Key qualitative predictor variables include `cap.shape`, the shape of the mushroom cap; `gill.color`, the color of the fungi gills, `stem.color`, the color of the mushroom stem; `habitat`, the habitat that the mushroom is grown/found; and `season`, the season that the mushroom is grown/found. The key for the levels of each categorical variable are described on the following page and in the data dictionary.

The data dictionary can be found here. There are 61069 total observations, each row represent a mushroom's physical features and also the environment it was found in.

Exploratory Data Analysis

Table 1: Distribution of Classes

class	n	percentage
e	27181	0.445
p	33888	0.555

Looking at the overall distribution of our response variable `class`, most of the mushrooms in our dataset seem to be poisonous ("p"). 33888 of the observations, or 55.5% of them are labeled poisonous, as opposed to 27181 (44.5%) of them as edible.

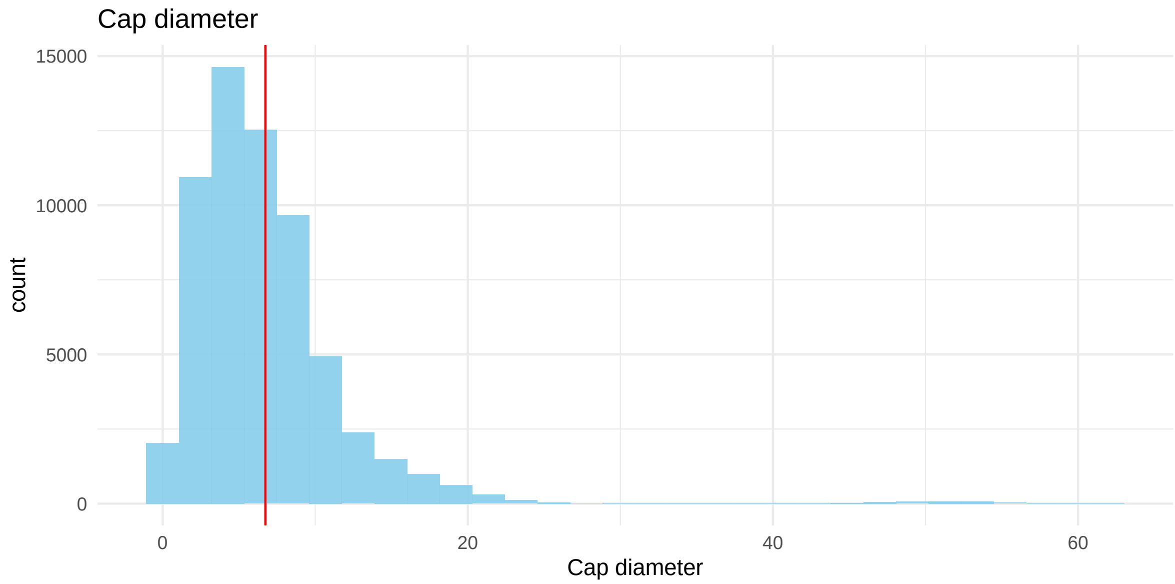


Table 2: cap diameter summary statistics

min	q1	median	q3	max	mean	sd
0.38	3.48	5.86	8.54	62.34	6.734	5.265

Visualizing the shape of our quantitative predictor, cap diameter, the distribution seems to be roughly unimodal, skewed right. The mean cap diameter is 6.734 cm, with a standard deviation of 5.265 cm.

Since the rest of our predictors our qualitative, we report their distributions through the tables below:

	bell	conical	flat	other	spherical	sunken	convex
cap.shape	b	c	f	o	p	s	x
percentage	0.093	0.030	0.219	0.057	0.043	0.117	0.441

	buff	red	gray	black	blue	brown	orange	pink	green	purple	white	yellow
cap.color	b	e	g	k	l	n	o	p	r	u	w	y
percentage	0.020	0.066	0.072	0.021	0.014	0.397	0.060	0.028	0.029	0.028	0.126	0.140

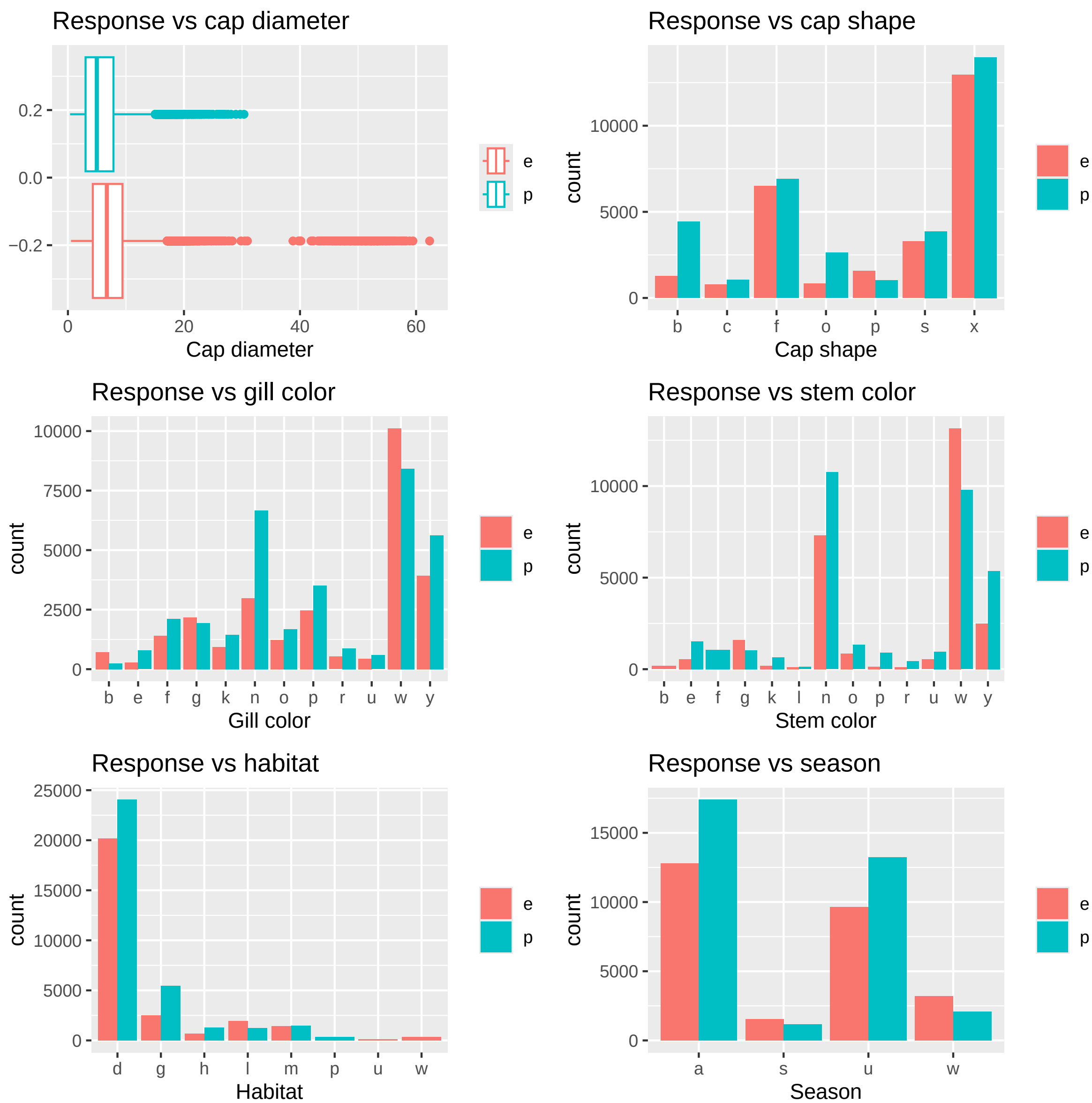
	woods	grasses	heaths	leaves	meadows	paths	urban	waste
habitat	d	g	h	l	m	p	u	w
percentage	0.724	0.130	0.033	0.052	0.048	0.006	0.002	0.006

	autumn	spring	summer	winter
season	a	s	u	w
percentage	0.494	0.045	0.375	0.086

	buff	red	none	gray	black	blue	brown	orange	pink	green	purple	white	yellow
stem.color	b	e	f	g	k	l	n	o	p	r	u	w	y
percentage	0.003	0.034	0.017	0.043	0.014	0.004	0.296	0.036	0.017	0.009	0.024	0.375	0.129

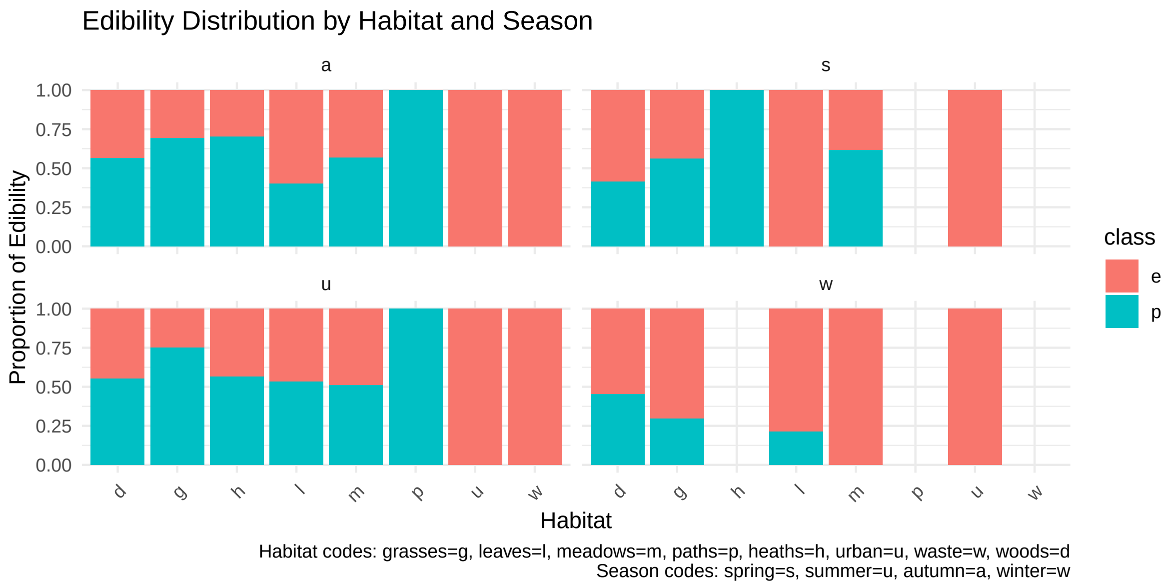
	buff	red	none	gray	black	brown	orange	pink	green	purple	white	yellow
gill.color	b	e	f	g	k	n	o	p	r	u	w	y
percentage	0.016	0.017	0.058	0.067	0.039	0.158	0.048	0.098	0.023	0.017	0.303	0.156

For qualitative variables, there appears to be more common physical and environmental characteristics. For example, for cap shape, flat and convex tends to be the most common; for stem color the most common is white, yellow, and brown; for habitat, woods is the most common. Thus, there are also characteristics which happen to be rarer, yet for some reason, natural selection has decided to preserve. These characteristics may have evolutionary advantageous properties (such as being poisonous), and we hope that they help us in our logistic regression model.



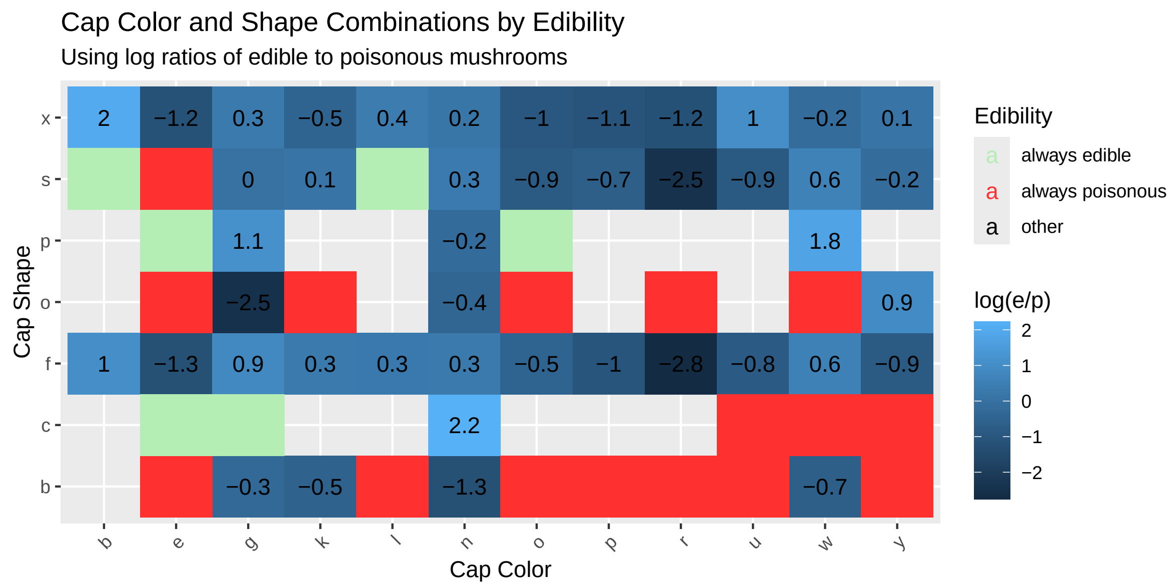
Looking at this bivariate exploratory data analysis, we see that, on average, smaller cap diameters seem to be correlated with poisonous mushrooms. We also observe some categories with a large disparity between the number of edible and number of poisonous mushrooms, offering potential modeling power. For example, if we randomly select a mushroom with a cap shape of convex, bell, or others, it is more likely to be poisonous/toxic than edible. Similarly, we see that mushrooms with gill color of brown and yellow tends to be poisonous. However, in many cases, it is hard to accurately predict whether a mushroom is edible or poisonous based off just one characteristic, suggesting our model needs to incorporate multiple predictors and/or interaction terms.

One interaction term we were interested in looking at is `habitat*season`. Mushrooms that grow in the same habitat may have different toxicity classification depending on if being poisonous is needed to defend against predators. The number of predators themselves may vary depending on season, so season may change how habitat affects the log-odds of whether the mushroom is edible or poisonous.



Looking at this graph, we see that mushrooms in certain habitats might only be edible during specific seasons. For example, mushrooms in the meadows are edible exclusively in the winter, but may be poisonous in other seasons. This suggests we may want to incorporate this interaction term into our final model.

We were also interested in looking at the interaction between cap color and cap shape, as these are two of the characteristics which are most apparent to a potential predator and natural selection may have led to some traits evolving together.



As the heatmap shows, certain combinations of cap color and cap shape are always edible or poisonous. Additionally, the log ratios across combinations of cap colors and cap sizes are varied with no pattern – for a mushroom with a sunken cap shape, it could be always edible (if the color is buff) to always poisonous (if the color is red). Similarly, if a mushroom is brown, it could be high likely it is edible (if the cap shape is conical) or likely it is poisonous (if the cap shape is bell). Thus, we may have to consider this interaction effect in our final model.

Methodology/Analysis

Model Assumption:

Based of our goals, a logistic regression was used. Below are the assumptions necessary for a logistic regression fit.

-Linearity: The log-odds appears to have a linear relationship with the quantitative predictor (see appendix).

-Randomness: The data were curated randomly in different places in North America, and thus we assume this condition is met.

-Independence: The observations are collected over a period of time, but in different regions and locations. For our analysis we assumed independent was met as the period did not span several years.

The base model:

$$\log\left(\frac{\mathrm{P(class = poisonous)}}{\mathrm{P(class = edible)}}\right) = \beta_0 + \beta_1 \cdot \mathrm{cap.diameter} + \beta_2 \cdot \mathrm{season} + \beta_3 \cdot \mathrm{cap.shape} + \beta_4 \cdot \mathrm{cap.color} + \beta_5 \cdot \mathrm{gill.color} + \beta_6 \cdot \mathrm{ste}$$

Predictor terms were chosen from the EDA and general physical or environmental factors that are generally understood and easy to evaluate by everyone. To determine if any predictors may not useful, we looked at coefficients from the tidy function with p-values greater than 0.01

term	estimate	std.error	statistic	p.value
(Intercept)	-15.328	172.082	-0.089	0.929
seasonu	0.003	0.020	0.156	0.876
cap.shapeo	0.173	0.077	2.253	0.024
gill.colorg	0.226	0.101	2.227	0.026
stem.colore	16.299	172.082	0.095	0.925
stem.colorf	31.777	185.273	0.172	0.864
stem.colorg	14.813	172.082	0.086	0.931
stem.colork	17.654	172.082	0.103	0.918
stem.colorl	14.725	172.082	0.086	0.932
stem.colorn	16.180	172.082	0.094	0.925
stem.coloro	15.797	172.082	0.092	0.927
stem.colorp	17.598	172.082	0.102	0.919
stem.colorr	16.734	172.082	0.097	0.923
stem.coloru	16.325	172.082	0.095	0.924
stem.colorw	15.400	172.082	0.089	0.929
stem.colory	16.390	172.082	0.095	0.924
habitath	0.053	0.054	0.987	0.324
habitatp	15.871	121.020	0.131	0.896
habitatu	-15.782	215.397	-0.073	0.942
habitatw	-16.260	126.274	-0.129	0.898

The Wald's Significance Tests for coefficients of multiple categories of the same predictor variables reveals that for certain categories there may be limited data (also seen through EDA) and/or limited predictive power. For simplicity of our model, we combine these categories into a general "Other" category. For example, `stem.color` of "w", "y", and "n" were kept while the other observations were assigned to a general "Other" category. For habitat, "d" and "g" were kept.

Running a likelihood ratio test to evaluate the overall significance of the coefficients of the new model with modified categorical variables, we have:

term	residual.deviance	df	deviance	p.value
class_binary ~ 1	83921.51	NA	NA	NA
class_binary ~ cap.diameter + season + cap.shape + cap.color + gill.color + stem.color.modified + habitat.modified	70569.07	37	13352.44	0

$$H_0 : \beta_j = 0 H_a : \beta_j \neq 0 \ for \ at \ least \ 1 \ j$$

Since the p-value is small, and less than $\alpha = 0.05$, we reject the H_0. The data provide sufficient evidence of at least one non-zero coefficient in the model. The model coefficients and corresponding inferential statistics for our main model are shown in the appendix (see Table 13).

Interactive Terms

As shown on our EDA, we hypothesized there may be some potential interaction terms. To determine the need for them in our model, we performed a drop in deviance test with the added interaction terms of `habitat*season` and `cap.shape*cap.color`.

term	residual.deviance	df	deviance	p.value
class_binary ~ cap.diameter + season + cap.shape + cap.color + gill.color + stem.color.modified + habitat.modified	70569.07	NA	NA	NA
class_binary ~ cap.diameter + season + cap.shape + cap.color + gill.color + stem.color.modified + habitat.modified + habitat.modified * season + cap.shape * cap.color	65170.76	54	5398.315	0

Since the p-value is low below $\alpha = 0.05$, we decide to include these interaction terms as there is convincing evidence that at least one of these interactive term coefficients are not 0 and thus helpful in the model.

Additionally for the base model, the AIC is 7.06×10^4 and the BIC is 7.1×10^4, whereas for the model with interaction effects, the AIC is 6.54×10^4 and the BIC is 6.62×10^4. For both measures, the full model performs better (lower AIC/BIC).

Model Results

Final Model

log(Odds(class = poisonous) = $\beta_0 + \beta_1 \cdot$cap.diameter$+\beta_2 \cdot$season$+\beta_3 \cdot$cap.shape$+\beta_4 \cdot$cap.color$+\beta_5 \cdot$gill.color$+\beta_6 \cdot$ste

Full model coefficient can be seen in appendix (see Table 14).

Coefficient Interpretation:

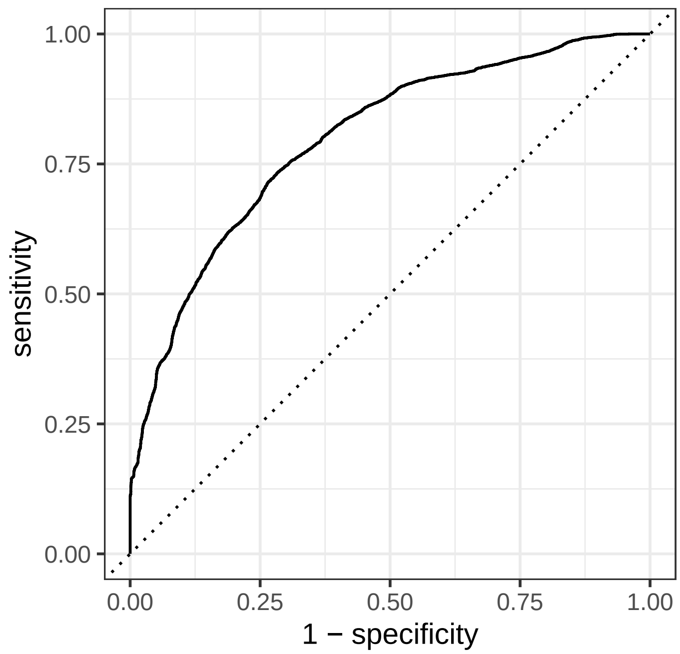
Below highlights some interesting coefficients for foragers to use to help them identify mushrooms that are more likely to be edible.

- The coefficient for cap diameter is -0.060, which means that for each 1 cm increase in the cap diameter, we expect the odds of the mushroom being poisonous multiplies by a factor of 0.9417645, holding all else constant. In terms of odds, an increase in cap diameter decreases the odds of the mushroom being poisonous so the larger the cap diameter is the less likely the mushroom is poisonous.

- The coefficient for cap shape p is -2.140. This suggests that, for mushrooms with a spherical cap shape (represented by "p"), we expect the odds of the mushroom being poisonous are 0.1176548 times the odds of being poisonous for mushrooms of bell shaped (baseline), granted all else are held constant. This value is also called the adjusted odds ratio. The odds of the mushroom being poisonous decrease significantly when the cap shape is "p" compared to the baseline and is also evident in the bivariate EDA as when cap shape is "bell", the mushroom tends to be poisonous.

- The coefficient for the interaction term season(w) * habitat.modified(g) is -1.026. This indicates that the combination of specific season (winter) and habitat (grasses) conditions modifies the expected odds of the mushroom being poisonous by a multiplicity factor of 0.3584378 times the odds of the mushroom being poisonous through an additive model of the same combination, while holding all other variables constant. This trend can be seen in the interactive term EDA as when season is winter and habitat is grasses we are more likely to observe an edible mushroom.

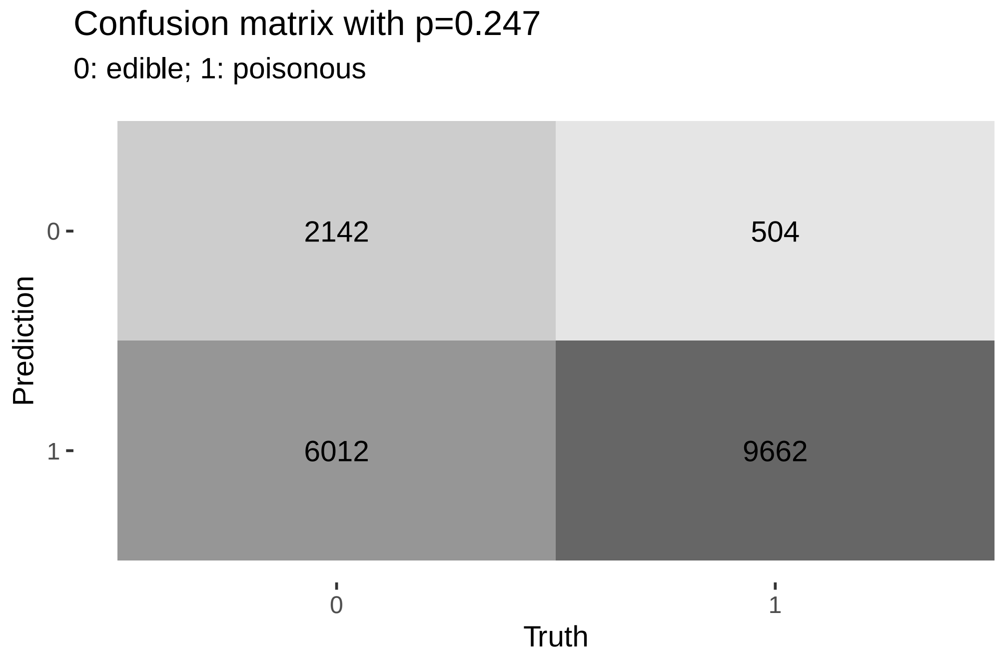
ROC curve




```
# A tibble: 1 x 3
  .metric .estimator .estimate
  <chr>   <chr>          <dbl>
1 roc_auc binary         0.797
```

```
# A tibble: 2 x 3
  .threshold specificity sensitivity
       <dbl>       <dbl>       <dbl>
1      0.247       0.263       0.950
2      0.247       0.263       0.950
```

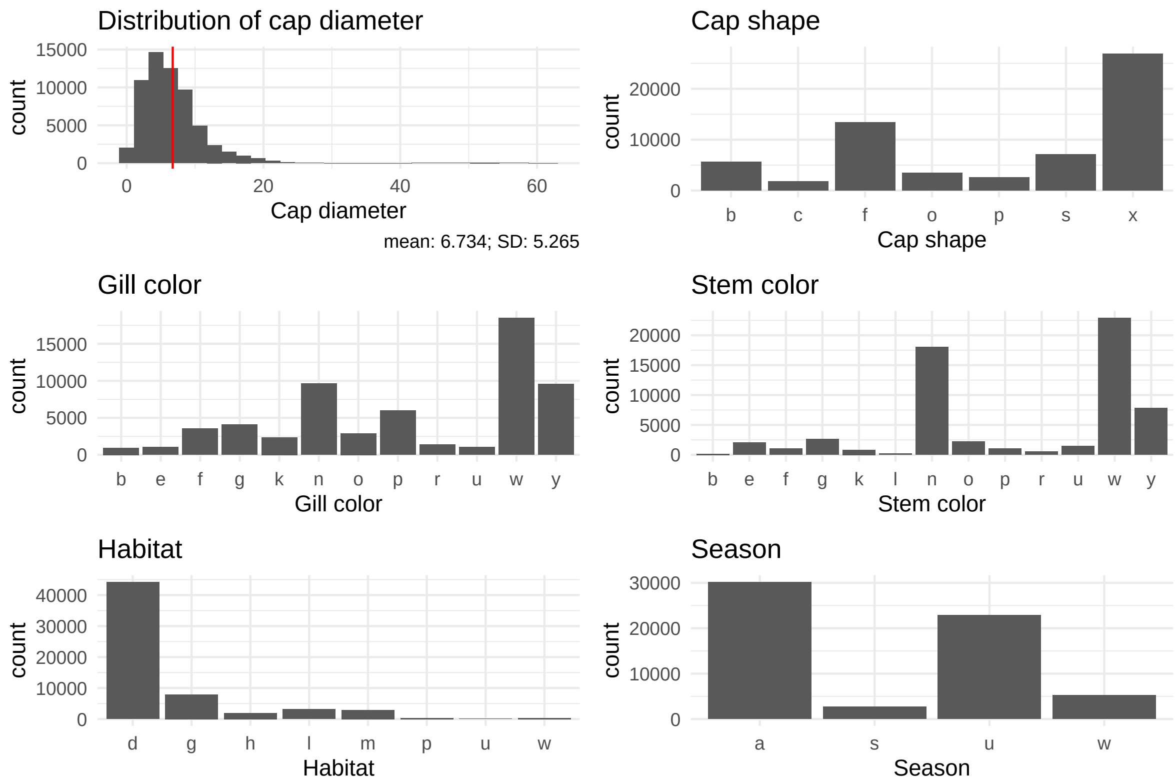
The model is decent as the AUC is 0.797 which is closer to 1 than 0.5. We decided on a threshold of p = 0.247 to achieve a sensitivity of 95%, since we wanted to prioritize minimizing false negatives, which are more expensive – better to be careful than eat a poisonous mushroom classified as "edible".



Using this threshold, we can evaluate our model's performance with a confusion matrix. As desired, for poisonous mushrooms, we are able to successfully classify 95% of them as poisonous. Our model struggles at correctly identifying mushrooms which are actually edible as edible, with a false positive rate of 73.7%. We were able to build a model that overall does much better (see appendix). However, this model requires many more variables, and becomes much more complex. For the purposes of this model, we wanted it to be applicable even in situations where humans found themselves having to assess edibility without many special tools or knowledge.

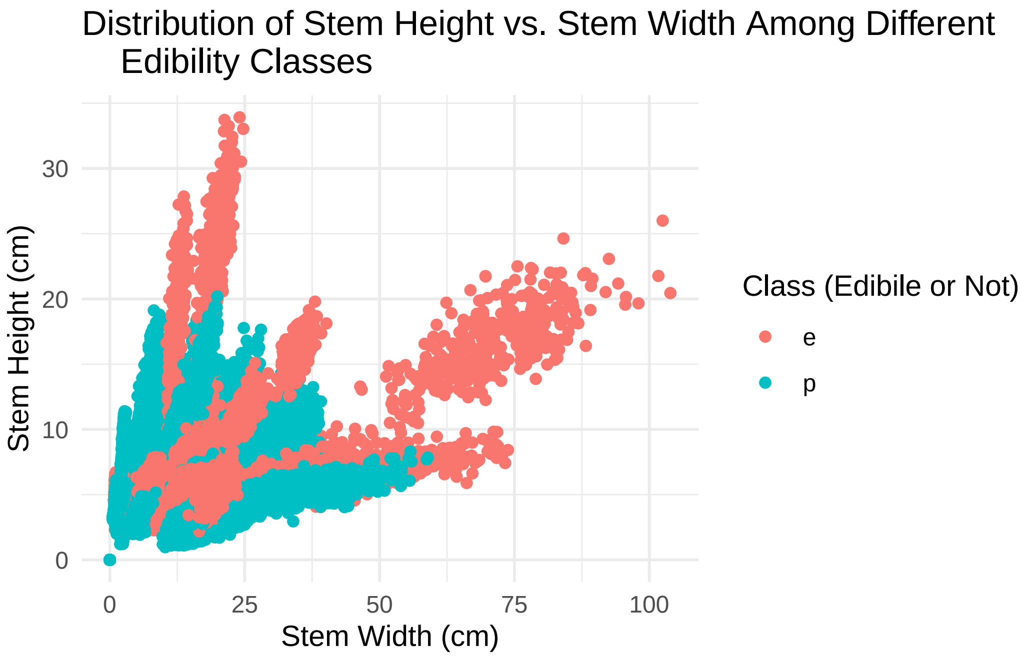
Conclusion

Appendix



cap shape: bell=b, conical=c, convex=x, flat=f, sunken=s, spherical=p, others=o
colors: brown=n, buff=b, gray=g, green=r, pink=p, purple=u, red=e, white=w, yellow=y, blue=l, orange=o, black=k
habitat: grasses=g, leaves=l, meadows=m, paths=p, heaths=h, urban=u, waste=w, woods=d
season: spring=s, summer=u, autumn=a, winter=w

Here is our original univariate EDA with the full visualizations.



Here, we look at multivariate exploratory data analysis including 2 predictors and our response variable. We visualize the effect of both stem width and stem height on the response variable, class. Interestingly, it seems like mushrooms with either high stem width or stem height seem to be edible. This suggests there may be some potential interaction effects between stem height and stem width – the low value of one alone does not seem to predict if the mushroom is poisonous, but requires the low value of both. However, in our model when we added this interaction effect, the performance did not include that drastically, and we deemed it more important to keep the model parsimonious as possible. Additionally, quantitative features can be hard to measure, and so may be less practical when serving as a general guideline for foraging mushrooms.

term	df.residual	residual.deviance	df	deviance	p.value
class_binary ~ cap.diameter + season + cap.shape + cap.color + gill.color + habitat + stem.root * stem.color + veil.type + veil.color + has.ring + ring.type + cap.shape * cap.color + habitat * season	60923	47301.04	NA	NA	NA
class_binary ~ cap.diameter + season + cap.shape + cap.color + gill.color + habitat + stem.root * stem.color + veil.type + veil.color + has.ring * ring.type + gill.attachment * gill.spacing + cap.shape * cap.color + habitat * season	60905	41107.65	18	6193.389	0

```
[1] "The AIC for the first model is: 47593.04, while the AIC for second model is: 41435.65. T
```

Here, we played with adding more predictors to our model. We do achieve better ROC curves with these as well, but we decided that a smaller model would still be better, and that many of these predictors that we added here may be hard to identify for the average person.

Table 13: Final Main Model Coefficients

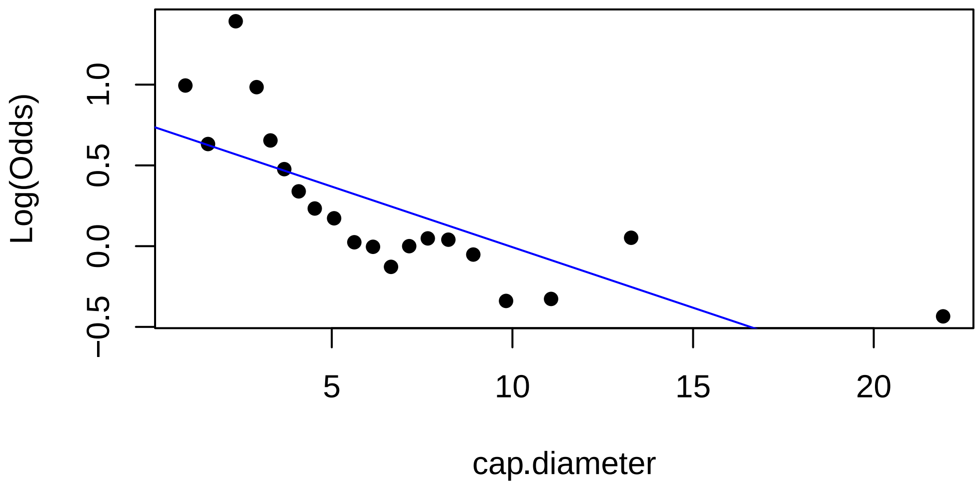
term	estimate	std.error	statistic	p.value
(Intercept)	0.590	0.111	5.333	0.000
cap.diameter	-0.074	0.002	-36.247	0.000
seasons	-0.975	0.049	-20.006	0.000
seasonu	-0.005	0.020	-0.243	0.808
seasonw	-0.766	0.035	-21.870	0.000
cap.shapec	-0.881	0.064	-13.674	0.000
cap.shapef	-1.155	0.042	-27.246	0.000
cap.shapeo	1.027	0.074	13.920	0.000
cap.shapep	-1.003	0.056	-17.825	0.000
cap.shapes	-1.082	0.047	-22.843	0.000
cap.shapex	-1.335	0.040	-33.690	0.000
cap.colore	1.989	0.087	22.762	0.000
cap.colorg	0.557	0.085	6.515	0.000
cap.colork	0.887	0.102	8.674	0.000
cap.colorl	0.650	0.109	5.971	0.000
cap.colorn	0.358	0.079	4.512	0.000
cap.coloro	1.359	0.088	15.402	0.000
cap.colorp	1.614	0.099	16.296	0.000
cap.colorr	2.886	0.109	26.419	0.000
cap.coloru	1.207	0.094	12.784	0.000
cap.colorw	0.821	0.082	9.975	0.000
cap.colory	0.771	0.083	9.311	0.000
gill.colore	1.262	0.117	10.767	0.000
gill.colorf	-0.247	0.104	-2.378	0.017
gill.colorg	0.222	0.097	2.302	0.021
gill.colork	0.936	0.102	9.165	0.000
gill.colorn	1.435	0.093	15.498	0.000
gill.coloro	0.720	0.098	7.350	0.000
gill.colorp	0.983	0.094	10.476	0.000
gill.colorr	0.696	0.110	6.354	0.000
gill.coloru	0.867	0.113	7.701	0.000
gill.colorw	0.548	0.090	6.096	0.000
gill.colory	0.971	0.092	10.562	0.000
stem.color.modifiedOther	-0.128	0.030	-4.339	0.000
stem.color.modifiedw	-0.744	0.025	-29.649	0.000
stem.color.modifiedy	0.224	0.035	6.391	0.000
habitat.modifiedg	0.471	0.031	15.277	0.000
habitat.modifiedOther	-0.341	0.027	-12.391	0.000

Table 14: Final Interactive Model Coefficients

term	estimate	std.error	statistic	p.value
(Intercept)	15.736	169.081	0.093	0.926
cap.diameter	-0.060	0.002	-24.569	0.000
seasons	-1.155	0.066	-17.548	0.000
seasonu	-0.001	0.024	-0.031	0.975
seasonw	-0.551	0.041	-13.496	0.000
cap.shapec	1.031	219.970	0.005	0.996
cap.shapef	-16.156	169.081	-0.096	0.924
cap.shapeo	-16.219	169.081	-0.096	0.924
cap.shapep	-2.140	0.144	-14.870	0.000
cap.shapes	-32.263	535.647	-0.060	0.952
cap.shapex	-17.544	169.081	-0.104	0.917
cap.colore	1.412	413.344	0.003	0.997
cap.colorg	-15.703	169.081	-0.093	0.926
cap.colork	-16.227	169.081	-0.096	0.924
cap.colorl	1.198	443.343	0.003	0.998
cap.colorn	-14.905	169.081	-0.088	0.930
cap.coloro	0.776	345.966	0.002	0.998
cap.colorp	1.607	399.972	0.004	0.997
cap.colorr	1.206	362.511	0.003	0.997
cap.coloru	1.308	390.015	0.003	0.997
cap.colorw	-15.077	169.081	-0.089	0.929
cap.colory	1.097	0.166	6.621	0.000
gill.colore	1.508	0.126	11.966	0.000
gill.colorf	-0.409	0.118	-3.459	0.001
gill.colorg	0.666	0.108	6.170	0.000
gill.colork	1.382	0.113	12.243	0.000
gill.colorn	1.650	0.104	15.937	0.000
gill.coloro	1.083	0.109	9.924	0.000
gill.colorp	1.244	0.105	11.860	0.000
gill.colorr	0.085	0.126	0.672	0.502
gill.coloru	1.330	0.128	10.427	0.000
gill.colorw	0.899	0.101	8.913	0.000
gill.colory	1.227	0.102	11.979	0.000
stem.color.modifiedOther	-0.062	0.032	-1.972	0.049
stem.color.modifiedw	-0.871	0.026	-32.937	0.000
stem.color.modifiedy	0.284	0.037	7.769	0.000
habitat.modifiedg	0.407	0.045	9.090	0.000
habitat.modifiedOther	-0.259	0.040	-6.507	0.000
seasons:habitat.modifiedg	0.027	0.173	0.156	0.876

term	estimate	std.error	statistic	p.value
seasonu:habitat.modifiedg	0.283	0.063	4.462	0.000
seasonw:habitat.modifiedg	-1.026	0.122	-8.410	0.000
seasons:habitat.modifiedOther	0.363	0.148	2.455	0.014
seasonu:habitat.modifiedOther	-0.143	0.060	-2.390	0.017
seasonw:habitat.modifiedOther	-0.925	0.125	-7.412	0.000
cap.shapec:cap.colore	-36.577	668.979	-0.055	0.956
cap.shapef:cap.colore	0.220	413.344	0.001	1.000
cap.shapeo:cap.colore	18.278	498.350	0.037	0.971
cap.shapep:cap.colore	-31.905	625.853	-0.051	0.959
cap.shapes:cap.colore	32.214	685.439	0.047	0.963
cap.shapex:cap.colore	1.203	413.344	0.003	0.998
cap.shapec:cap.colorg	-16.785	567.768	-0.030	0.976
cap.shapef:cap.colorg	15.398	169.081	0.091	0.927
cap.shapeo:cap.colorg	19.802	169.081	0.117	0.907
cap.shapep:cap.colorg	1.377	0.219	6.288	0.000
cap.shapes:cap.colorg	32.125	535.647	0.060	0.952
cap.shapex:cap.colorg	17.142	169.081	0.101	0.919
cap.shapec:cap.colork	NA	NA	NA	NA
cap.shapef:cap.colork	16.314	169.081	0.096	0.923
cap.shapeo:cap.colork	34.895	342.679	0.102	0.919
cap.shapep:cap.colork	NA	NA	NA	NA
cap.shapes:cap.colork	32.985	535.647	0.062	0.951
cap.shapex:cap.colork	18.507	169.081	0.109	0.913
cap.shapec:cap.colorl	NA	NA	NA	NA
cap.shapef:cap.colorl	-0.922	443.343	-0.002	0.998
cap.shapeo:cap.colorl	NA	NA	NA	NA
cap.shapep:cap.colorl	NA	NA	NA	NA
cap.shapes:cap.colorl	-1.799	902.221	-0.002	0.998
cap.shapex:cap.colorl	0.280	443.343	0.001	0.999
cap.shapec:cap.colorn	-4.771	219.970	-0.022	0.983
cap.shapef:cap.colorn	14.639	169.081	0.087	0.931
cap.shapeo:cap.colorn	16.140	169.081	0.095	0.924
cap.shapep:cap.colorn	1.569	0.163	9.651	0.000
cap.shapes:cap.colorn	30.949	535.647	0.058	0.954
cap.shapex:cap.colorn	16.049	169.081	0.095	0.924
cap.shapec:cap.coloro	NA	NA	NA	NA
cap.shapef:cap.coloro	-0.430	345.966	-0.001	0.999
cap.shapeo:cap.coloro	17.829	444.909	0.040	0.968
cap.shapep:cap.coloro	-31.349	574.066	-0.055	0.956
cap.shapes:cap.coloro	16.579	614.835	0.027	0.978
cap.shapex:cap.coloro	1.365	345.966	0.004	0.997

term	estimate	std.error	statistic	p.value
cap.shapec:cap.colorp	NA	NA	NA	NA
cap.shapef:cap.colorp	-0.371	399.972	-0.001	0.999
cap.shapeo:cap.colorp	NA	NA	NA	NA
cap.shapep:cap.colorp	NA	NA	NA	NA
cap.shapes:cap.colorp	15.244	646.767	0.024	0.981
cap.shapex:cap.colorp	0.870	399.972	0.002	0.998
cap.shapec:cap.colorr	NA	NA	NA	NA
cap.shapef:cap.colorr	2.043	362.511	0.006	0.996
cap.shapeo:cap.colorr	17.198	460.562	0.037	0.970
cap.shapep:cap.colorr	NA	NA	NA	NA
cap.shapes:cap.colorr	17.697	624.294	0.028	0.977
cap.shapex:cap.colorr	2.058	362.511	0.006	0.995
cap.shapec:cap.coloru	-0.903	573.567	-0.002	0.999
cap.shapef:cap.coloru	-0.367	390.015	-0.001	0.999
cap.shapeo:cap.coloru	NA	NA	NA	NA
cap.shapep:cap.coloru	NA	NA	NA	NA
cap.shapes:cap.coloru	15.779	640.657	0.025	0.980
cap.shapex:cap.coloru	-0.761	390.015	-0.002	0.998
cap.shapec:cap.colorw	16.299	317.549	0.051	0.959
cap.shapef:cap.colorw	15.174	169.081	0.090	0.928
cap.shapeo:cap.colorw	34.217	227.081	0.151	0.880
cap.shapep:cap.colorw	NA	NA	NA	NA
cap.shapes:cap.colorw	31.121	535.647	0.058	0.954
cap.shapex:cap.colorw	17.000	169.081	0.101	0.920
cap.shapec:cap.colory	NA	NA	NA	NA
cap.shapef:cap.colory	-0.221	0.199	-1.116	0.265
cap.shapeo:cap.colory	NA	NA	NA	NA
cap.shapep:cap.colory	NA	NA	NA	NA
cap.shapes:cap.colory	15.562	508.261	0.031	0.976
cap.shapex:cap.colory	NA	NA	NA	NA




```
# A tibble: 7 x 5
  class_binary cap.shape     n  prop emp_logit
         <dbl> <chr>     <int> <dbl>     <dbl>
1            1 b          3103 0.777    1.25
2            1 c           688 0.561    0.244
3            1 f          4839 0.516    0.0636
4            1 o          1907 0.768    1.20
5            1 p           713 0.396   -0.421
6            1 s          2704 0.539    0.157
7            1 x          9768 0.518    0.0725
```

```
# A tibble: 12 x 5
   class_binary gill.color     n  prop emp_logit
          <dbl> <chr>      <int> <dbl>     <dbl>
 1            1 b            159 0.247    -1.12
 2            1 e            549 0.738     1.04
 3            1 f           1550 0.607     0.434
 4            1 g           1357 0.472    -0.113
 5            1 k            998 0.610     0.446
 6            1 n           4694 0.695     0.823
 7            1 o           1204 0.593     0.374
 8            1 p           2422 0.580     0.324
```

```
 9           1 r            590 0.624     0.508
10           1 u            413 0.569     0.277
11           1 w           5842 0.450    -0.202
12           1 y           3944 0.591     0.370
```

```
# A tibble: 4 x 5
  class_binary stem.color.modified     n  prop emp_logit
         <dbl> <chr>               <int> <dbl>     <dbl>
1            1 Other                5622 0.652     0.628
2            1 n                    7550 0.597     0.394
3            1 w                    6768 0.424    -0.307
4            1 y                    3782 0.686     0.779
```

```
# A tibble: 3 x 5
  class_binary habitat.modified     n  prop emp_logit
         <dbl> <chr>            <int> <dbl>     <dbl>
1            1 Other             3098 0.490   -0.0396
2            1 d                16875 0.546    0.185
3            1 g                 3749 0.679    0.747
```

```
# A tibble: 4 x 5
  class_binary season     n  prop emp_logit
         <dbl> <chr>  <int> <dbl>     <dbl>
1            1 a      12143 0.576     0.305
2            1 s        825 0.440    -0.239
3            1 u       9319 0.579     0.317
4            1 w       1435 0.390    -0.448
```

Here is the calculated empirical logit plot for our only quantitative predictor variable and it appears to generally fit the linearity assumption. For the other qualitative predictor variables the emperical logic was calculated for the training dataset.

References

Brandenburg, William E., and Karlee J. Ward. 2018. "Mushroom Poisoning Epidemiology in the United States." *Mycologia* 110 (4): 637–41. https://doi.org/10.1080/00275514.2018.1479561.