DIGI EDU HACK 2023

DIGIEDUHACK SOLUTION CANVAS

Title of the solution:	
Challenge addressed:	
Team name:	
Challenge category:	

Solution description

Please describe your solution, its main elements and objectives as well as a brief implementation plan with some key overall milestones, resources required and eventual barriers foreseen. What is your final product/service/tool/activity? How could the solution be used to enhance digital education in the your challenge area? How could the successof the solution be measured? How will the solution provide benefits to the challenge owner?

Context

What is the problem you are facing?
What is the challenge that you are solving?

Target group

Who is the target group for your solution?
Who will this solution affect and how?
How will they benefit?

Impact

What is the impact of your solution? How do you measure it?

Describe it in a tweet

Describe your solution in a short catchy way in maximum 280 characters

How to use drone image & GIS to recreate your city in minecraft? Drone tech & machine learning brings education & participatory urban planning to whole new level!
#Dronecraft #Drone4Edu

Innovativeness

What makes your solution different and original?
Can anything similar be found on themarket? How innovative is it?

Transferability

Can your solution be used in other contexts?
What parts of it can be applied to other context?

Sustainability

What is your plan for the implementation of the solution and how do you see it in the mid- and long term?

Team work

Explain why you are the perfect team to develop this work and what are the competencies you all bring in so the solution is developed successfully. How well did you work as a team?
Could you continue to work as a team in the future?

Title: Leveraging Drone Technology for Integrated Environmental Mapping and Minecraft Visualization

Context:

In an era dominated by technological advancements, the intersection of drones, GIS (Geographic Information System), and video games presents a groundbreaking opportunity for immersive and interactive educational experiences. This project seeks to utilize drone technology for aerial data collection and subsequent integration with GIS and Minecraft for educational, urban planning, public engagement, academic research, and government public consultation purposes.

Target:

The primary target audience includes urban planners, researchers, municipal governments, planning authorities, students, children, and elderly.

Public actors are able to instrumentalize the tool to facilitate the engagement of the laymen in participatory planning exercises.

Community organizations can initiate co-creation workshops and formulate land-use planning proposals with the input of community members through gaming.

Children and the **elderly** with limited technical knowledge and/or digital literacy can be empowered by the tool in contributing their ideas to land use planning.

This innovative solution aims to provide a comprehensive and accessible platform for understanding and interacting with geographical data by way of gamification, allowing for a more equitable and creative public engagement pathway to land-use planning.

Solution:

The process involves using drones to collect high-resolution footage and images of the urban built environment, followed by data processing in ArcGIS to categorize and label various geographical and urban landscape features. The creation of a fishnet grid aids in organizing the data spatially. This data is then imported into Minecraft, offering a visually immersive experience where users, particularly laymen such as children, the elderly, and local inhabitants, can explore and interact with a digital replica of the real-world environment. Urban planners who wish to collect ideas and inputs from the general public can capitalize the gaming experience to gather feedback and counter-proposals, supporting deliberative processes. Urban planning workshops and consultation sessions can be held at the community level with the aid of the tool in order to incentivize public participation of those who often experience exclusion from the institutional decision-making mechanism.

Educators can design pedagogical exercises with the tool to encourage peer-to-peer learning for subjects like geography, urban design, and public space.

Impact:

The quality of public engagement in land-use planning processes is alleviated through interactive virtual environments, which is more digestible than blueprints and technical documents.

Urban planners can utilize the platform to harness the potential and creativity of the users and to create inclusive urban designs that cater the needs of different community members.

Disadvantaged groups, such as people with disabilities, women and girls, and racialized persons, can overcome accessibility barriers by interacting in a virtual space which reanimates the real-world environment, ensuring their right to participate in redesigning urban space.

Municipal governments, planning authorities, and public consultancy professionals can gain a powerful tool for transparent and inclusive decision-making, while increasing levels of participation, efficiency and accountability in urban planning.

In the education sector, **students** can gain hands-on experience with drone technologies and geodata processing methods, enhancing their STEM and problem-solving skills. **Academic researchers** benefit from a richer dataset of community perception and feedback related to land-use planning.

Innovativeness:

This project is innovative in its seamless integration of drone technology, GIS, and Minecraft. The combination of real-world data capture, spatial analysis, and immersive visualization can be used to communicate technical information to the public, provide access to information that was previously only provided to experts and governments, and crowdsource information and feedback directly from participants. The data collected from drone images reinforces tangibility and authenticity of the simulation. It further enables a bottom-up and community-based approach in land-use planning by lowering the knowledge threshold to land-use planning and reducing the accessibility barriers to use urban space. The tool can fill in the epistemological gap between planning practitioners and laymen, such as children and the elderly, through gamification.

Transferability:

The methodology employed is adaptable to various contexts and environments. It can be applied globally, regardless of climatic and cultural constraints, providing a versatile tool for education, planning, and research in different geographical and cultural settings. The use of drone technology and data processing software, when adequately applied, has the potential of minimizing the cost of recreating the built environment in the virtual space.

Sustainability:

The project's sustainability lies in its ability to evolve with technological advancements. As GIS and geodata processing technologies progress, the tool can be updated and expanded. Educational institutions, urban planning departments, and local governments can integrate this solution as a part of public consultation and participatory mechanism into their long-term land-use strategies for continuous benefit.

Teamwork:

The success of this project hinges on collaboration between drone operators, GIS specialists, software developers, educators, and urban planners. A multidisciplinary team ensures the seamless execution of each phase, from data collection to visualization.

In conclusion, this innovative integration of drone technology, GIS, and Minecraft holds immense potential for transformative educational experiences, urban planning, research, and public engagement. The project's adaptability, sustainability, and collaborative nature underscore its potential as a pioneering solution for diverse applications and audiences.

A park in Lima, Peru, in Minecraft and real life

Source: UN Habitat, USING MINECRAFT FOR YOUTH PARTICIPATION IN URBAN DESIGN AND GOVERNANCE, p.3
https://unhabitat.org/sites/default/files/download-manager-files/Using%20Minecraft%20for%20Youth%20Participation%20in%20Urban%20Design%20and%20Governance.pdf

Innovative Mapping: Aerial Intelligence Meets Virtual Realms for Education and Planning

Conn L.H. Lee

Samuel T.C.Kong

Context

In an era dominated by technological advancements, the intersection of drones, GIS (Geographic Information System), and video games presents a groundbreaking opportunity for immersive and interactive educational experiences.

This project seeks to utilize drone technology for aerial data collection and subsequent integration with GIS and Minecraft for educational, urban planning, public engagement, academic research, and government public consultation purposes.

By harmonizing cutting-edge technologies, this initiative pioneers a new frontier in education, urban planning, and public interaction. The synergy of drones, GIS, and Minecraft not only provides a novel educational platform but also empowers diverse stakeholders in shaping and understanding their environment, fostering a more engaged and informed society.

Target

The primary target audience includes urban planners, researchers, municipal governments, planning authorities, students, children, and elderly.

Public actors are able to instrumentalize the tool to facilitate the engagement of the laymen in participatory planning exercises.

Community organizations can initiate co-creation workshops and formulate land-use planning proposals with the input of community members through gaming.

Children and the **elderly** with limited technical knowledge and/or digital literacy can be empowered by the tool in contributing their ideas to land use planning.

This innovative solution aims to provide a comprehensive and accessible platform for understanding and interacting with geographical data by way of gamification, allowing for a more equitable and creative public engagement pathway to land-use planning.

Solution

The process involves using drones to collect high-resolution footage and images of the urban built environment, followed by data processing in ArcGIS to categorize and label various geographical and urban landscape features. The creation of a fishnet grid aids in organizing the data spatially. This data is then imported into Minecraft, offering a visually immersive experience where users, particularly laymen such as children, the elderly, and local inhabitants, can explore and interact with a digital replica of the real-world environment.

Urban planners who wish to collect ideas and inputs from the general public can capitalize the gaming experience to gather feedback and counter-proposals, supporting deliberative processes. Urban planning workshops and consultation sessions can be held at the community level with the aid of the tool in order to incentivize public participation of those who often experience exclusion from the institutional decision-making mechanism. **Educators** can design pedagogical exercises with the tool to encourage peer-to-peer learning for subjects like geography, urban design, and public space.

Impact

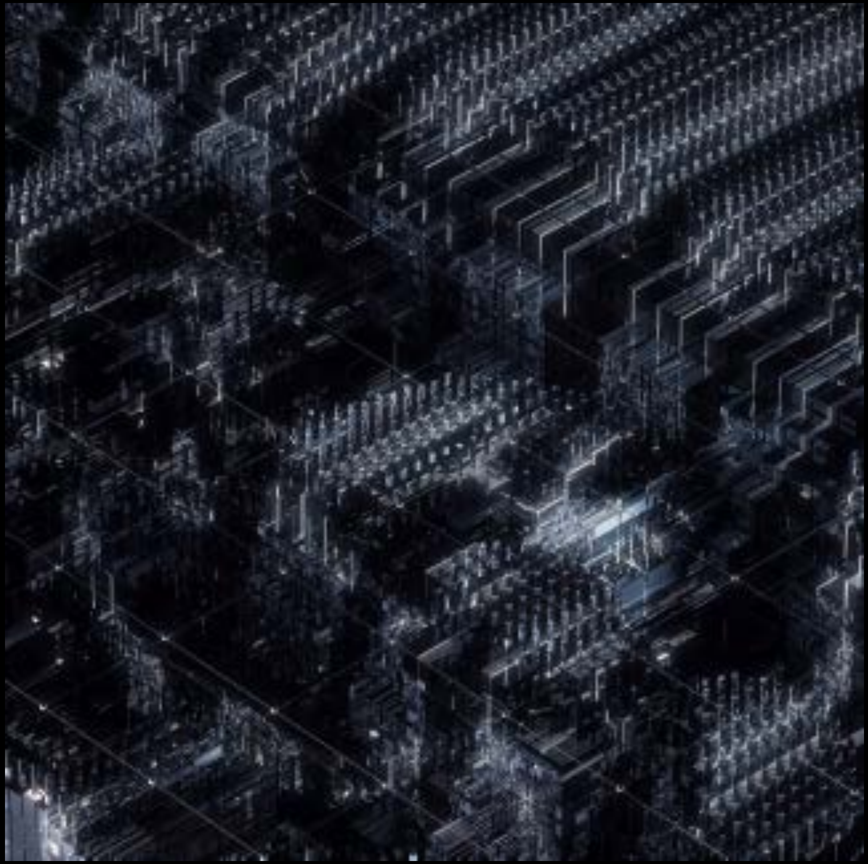
The quality of public engagement in land-use planning processes is alleviated through interactive virtual environments, which is more digestible than blueprints and technical documents.

Urban planners can utilize the platform to harness the potential and creativity of the users and to create inclusive urban designs that cater the needs of different community members.

Disadvantaged groups, such as people with disabilities, women and girls, and racialized persons, can overcome accessibility barriers by interacting in a virtual space which reanimates the real-world environment, ensuring their right to participate in redesigning urban space.

Municipal governments, planning authorities, and public consultancy professionals can gain a powerful tool for transparent and inclusive decision-making, while increasing levels of participation, efficiency and accountability in urban planning.

In the education sector, **students** can gain hands-on experience with drone technologies and geodata processing methods, enhancing their STEM and problem-solving skills. **Academic researchers** benefit from a richer dataset of community perception and feedback related to land-use planning.



Innovativeness

This project is innovative in its seamless integration of drone technology, GIS, and Minecraft. The combination of real-world data capture, spatial analysis, and immersive visualization can be used to communicate technical information to the public, provide access to information that was previously only provided to experts and governments, and crowdsource information and feedback directly from participants.

The data collected from drone images reinforces tangibility and authenticity of the simulation. It further enables a bottom-up and community-based approach in land-use planning by lowering the knowledge threshold to land-use planning and reducing the accessibility barriers to use urban space. The tool can fill in the epistemological gap between planning practitioners and laymen, such as children and the elderly, through gamification.

Transferability

The methodology employed is adaptable to various contexts and environments. It can be applied globally, regardless of climatic and cultural constraints, providing a versatile tool for education, planning, and research in different geographical and cultural settings.

The use of drone technology and data processing software, when adequately applied, has the potential of minimizing the cost of recreating the built environment in the virtual space.

This adaptable methodology transcends geographical and cultural boundaries, offering a universally applicable solution. By efficiently leveraging drone technology and data processing software, the initiative not only enhances global accessibility but also demonstrates economic efficiency, minimizing the financial investments required for virtual environment replication.

Sustainability

The project's sustainability lies in its ability to evolve with technological advancements. As GIS and geodata processing technologies progress, the tool can be updated and expanded.

Educational institutions, urban planning departments, and local governments can integrate this solution as a part of public consultation and participatory mechanism into their long-term land-use strategies for continuous benefit.

Furthermore, the diverse expertise within the collaborative team guarantees a nuanced understanding of each project facet, promoting efficiency and innovation.

With adaptability woven into its core, the project not only meets current needs but stands resilient in the face of evolving technological landscapes, ensuring a lasting impact on education, urban development, and societal engagement.

Team Work

The success of this project hinges on collaboration between drone operators, GIS specialists, software developers, educators, and urban planners. A multidisciplinary team ensures the seamless execution of each phase, from data collection to visualization.

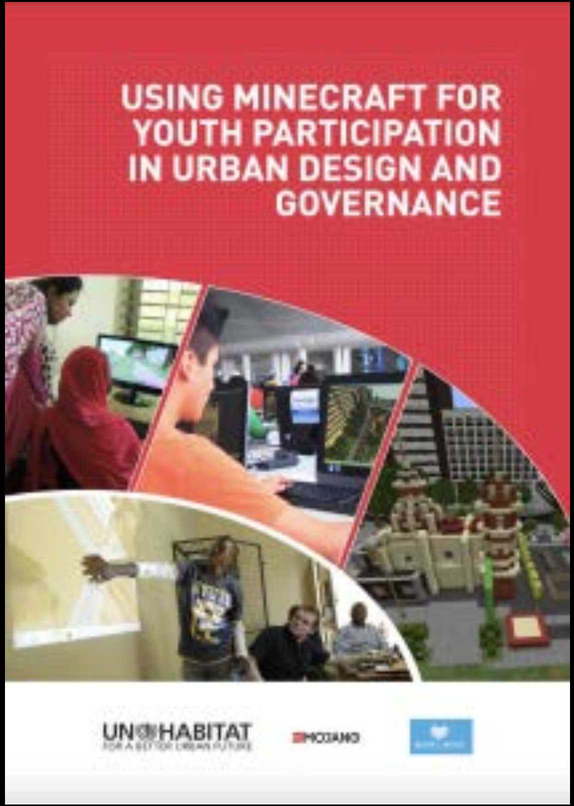
In conclusion, this innovative integration of drone technology, GIS, and Minecraft holds immense potential for transformative educational experiences, urban planning, research, and public engagement. The project's adaptability, sustainability, and collaborative nature underscore its potential as a pioneering solution for diverse applications and audiences.

This symbiotic collaboration not only enhances project efficiency but also reflects a forward-thinking approach to complex problem-solving. With adaptability ingrained, the initiative is poised to redefine educational paradigms, urban planning methodologies, and research landscapes while fostering inclusive public engagement. Its impact resonates across diverse sectors, promising a lasting and influential legacy.

Bridging the gap…

- UN Habitat has been experimenting with Minecraft for inclusive participation urban design since 2012.
- There is a great potential for gamification…

- Our tool tries to connect drone images with minecraft by developing an automated machine learning algorithm which processes and categorizes the data collected by drones.



Thank you!

Classify Building Conditions in Zanzibar from Drone Imagery

In [1]:
```
%reload_ext autoreload
%autoreload 2
%matplotlib inline
```

In [2]:
```
from fastai import *
from fastai.vision import *
```

In [4]:
```
from fastai.utils import *
show_install()
```

```
```text
=== Software ===
python version  : 3.6.6
fastai version  : 1.0.33
torch version   : 1.0.0.dev20181114
nvidia driver   : 410.48
torch cuda ver  : 9.2.148
torch cuda is   : available
torch cudnn ver : 7104
torch cudnn is  : enabled

=== Hardware ===
nvidia gpus     : 1
torch available : 1
  - gpu0        : 16278MB | Quadro P5000

=== Environment ===
platform        : Linux-4.4.0-130-generic-x86_64-with-debian-stretch-sid
distro          : #156-Ubuntu SMP Thu Jun 14 08:53:28 UTC 2018
conda env       : Unknown
python          : /opt/conda/envs/fastai/bin/python
sys.path        :
/opt/conda/envs/fastai/lib/python36.zip
/opt/conda/envs/fastai/lib/python3.6
/opt/conda/envs/fastai/lib/python3.6/lib-dynload
/opt/conda/envs/fastai/lib/python3.6/site-packages
/opt/conda/envs/fastai/lib/python3.6/site-packages/IPython/extensions
/root/.ipython
```

Please make sure to include opening/closing ``` when you paste into forum
s/github to make the reports appear formatted as code sections.

Optional package(s) to enhance the diagnostics can be installed with:
pip install distro
Once installed, re-run this utility to get the additional information
```

Prepare Data

In [5]:
```
path = Path('/storage/classify-data')
```

In [6]:
```
path_img = path/'images'
```

In [7]:
```
fnames = get_image_files(path_img)
print(len(fnames))
fnames[:5]
```

```
20176
```

Out[7]:
```
[PosixPath('/storage/classify-data/images/grid043_04750_Empty.jpg'),
 PosixPath('/storage/classify-data/images/grid058_05520_Empty.jpg'),
 PosixPath('/storage/classify-data/images/grid029_00149_Complete.jpg'),
 PosixPath('/storage/classify-data/images/grid042_02150_Empty.jpg'),
 PosixPath('/storage/classify-data/images/grid035_00463_Foundation.jpg')]
```

In [8]:
```
# filter out empty jpg files by size>0 and sort
fnames = [fname.name for fname in sorted(fnames) if os.path.getsize(fname)>0
print(len(fnames))
fnames[:5]
```

```
20176
```

Out[8]:
```
['grid001_00001_Complete.jpg',
 'grid001_00002_Complete.jpg',
 'grid001_00003_Complete.jpg',
 'grid001_00004_Complete.jpg',
 'grid001_00005_Complete.jpg']
```

In [9]:
```
df = pd.DataFrame(fnames,columns=['fnames'])
df.head()
```

Out[9]:

	fnames
0	grid001_00001_Complete.jpg
1	grid001_00002_Complete.jpg
2	grid001_00003_Complete.jpg
3	grid001_00004_Complete.jpg
4	grid001_00005_Complete.jpg

In [10]:
```
# hand-picked val grids
holdout_grids = ['grid028_','grid029_','grid042_','grid058_']
valid_idx = [i for i,o in df.iterrows() if any(c in str(o.fnames) for c in h
```

In [11]:
```
df.iloc[valid_idx].head()
```

Out[11]:

	fnames
7432	grid028_00000_Empty.jpg
7433	grid028_00001_Complete.jpg
7434	grid028_00002_Complete.jpg
7435	grid028_00003_Complete.jpg
7436	grid028_00004_Complete.jpg

In [12]:
```
# pulled out of fastai/data.py
pat = r'([^_]+).jpg$'
pat = re.compile(pat)
def get_label(fn): return pat.search(str(fn)).group(1)
```

In [13]:
```
src = (ImageItemList.from_df(df, folder='images', path=path)
        .split_by_idx(valid_idx)
        .label_from_func(get_label, classes=['Complete', 'Incomplete', 'Four
```

In [55]:
```
bs = 32
sz = 512
tfms = get_transforms(flip_vert=True, max_rotate=0.2, max_warp=0., max_zoom=
data = (src.transform(tfms, size=512, resize_method=ResizeMethod.SQUISH, pad
        .databunch(bs=bs)
        .normalize(imagenet_stats))
```

In [56]:
```
data
```

Out[56]:
```
ImageDataBunch;

Train: LabelList
y: CategoryList (14833 items)
[Category Complete, Category Complete, Category Complete, Category Complet
e, Category Complete]...
Path: /storage/classify-data
x: ImageItemList (14833 items)
[Image (3, 428, 920), Image (3, 184, 187), Image (3, 197, 196), Image (3,
157, 157), Image (3, 185, 188)]...
Path: /storage/classify-data;

Valid: LabelList
y: CategoryList (5343 items)
[Category Empty, Category Complete, Category Complete, Category Complete,
Category Complete]...
Path: /storage/classify-data
x: ImageItemList (5343 items)
[Image (3, 243, 179), Image (3, 298, 234), Image (3, 186, 221), Image (3,
300, 181), Image (3, 176, 184)]...
Path: /storage/classify-data;

Test: None
```

In [57]:
```
data.train_ds.classes
```

Out[57]:
```
['Complete', 'Incomplete', 'Foundation', 'Empty']
```

In [58]:
```
for i in range(5):
    print(data.valid_ds.classes[data.valid_ds.y[i].data], data.valid_ds.item
    data.valid_ds.x[i].show()
    plt.show()
```

Empty /storage/classify-data/images/grid028_00000_Empty.jpg

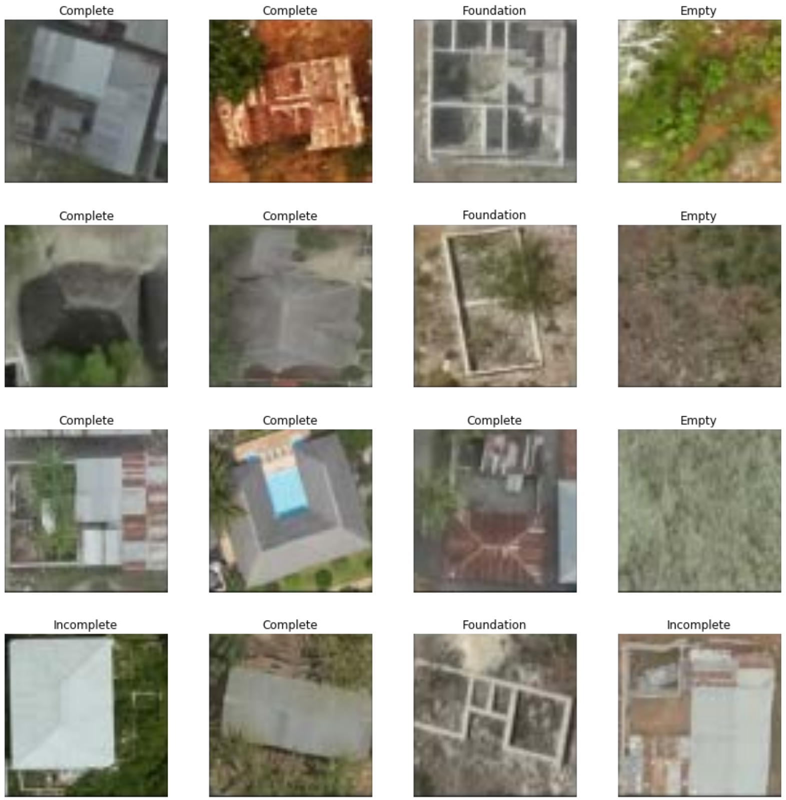
Complete /storage/classify-data/images/grid028_00001_Complete.jpg

Complete /storage/classify-data/images/grid028_00002_Complete.jpg

Complete /storage/classify-data/images/grid028_00003_Complete.jpg

```
Complete /storage/classify-data/images/grid028_00004_Complete.jpg
```

In [59]:
```python
data.show_batch(rows=4, figsize=(12,12))
```



In [60]:
```python
data.show_batch(rows=4, figsize=(12,12), ds_type=DatasetType.Valid)
```

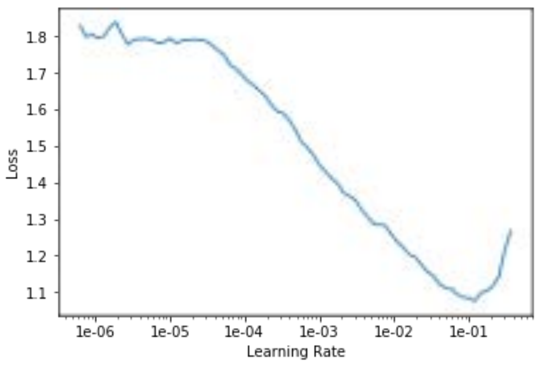
In [61]:
```python
data.loss_func
```

Out[61]:
```
<fastai.layers.FlattenedLoss at 0x7f5274a9d400>
```

In [63]:
```python
learn = create_cnn(data, models.resnet50, metrics=error_rate)
```

In [64]:
```
learn.lr_find()
learn.recorder.plot()
```

```
LR Finder is complete, type {learner_name}.recorder.plot() to see the grap
h.
```



In [65]:
```
lr = 1e-2
```

In [67]:
```
from fastai.callbacks import *

# small change to SaveModelCallback() to add printouts
@dataclass
class SaveModelCallbackVerbose(TrackerCallback):
    "A `TrackerCallback` that saves the model when monitored quantity is bes
    every:str='improvement'
    name:str='bestmodel'
    def __post_init__(self):
        if self.every not in ['improvement', 'epoch']:
            warn(f'SaveModel every {self.every} is invalid, falling back to
            self.every = 'improvement'
        super().__post_init__()

    def on_epoch_end(self, epoch, **kwargs:Any)->None:
        if self.every=="epoch": self.learn.save(f'{self.name}_{epoch}')
        else: #every="improvement"
            current = self.get_monitor_value()
            if current is not None and self.operator(current, self.best):
                self.best = current
                self.learn.save(f'{self.name}')
                print(f'saved model at epoch {epoch} with {self.monitor} val

    def on_train_end(self, **kwargs):
        if self.every=="improvement": self.learn.load(f'{self.name}')
```

In [68]:
```
learn.fit_one_cycle(10, max_lr=lr,
                    callbacks=[
                        SaveModelCallbackVerbose(learn,
                                                 monitor='error_rate',
                                                 mode='min',
                                                 name='20181206-rn50class-st
                    ]
                   )
```

Total time: 1:17:00

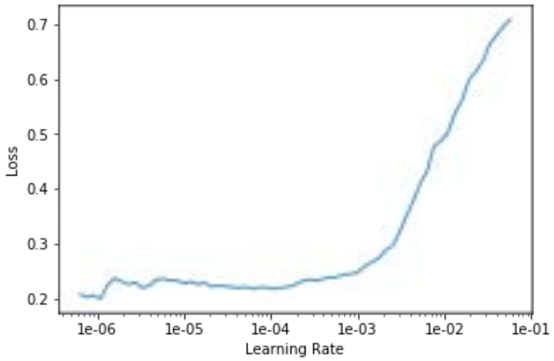
epoch	train_loss	valid_loss	error_rate
1	0.373114	0.239636	0.088153
2	0.364517	0.273235	0.092645
3	0.339809	0.367768	0.138686
4	0.336729	0.265249	0.097885
5	0.302687	0.227810	0.077859
6	0.299651	0.206304	0.073367
7	0.260983	0.184381	0.065693
8	0.259397	0.478516	0.064009
9	0.219406	0.172479	0.061576
10	0.227847	0.245279	0.061202

```
saved model at epoch 1 with error_rate value: 0.08815272152423859
saved model at epoch 5 with error_rate value: 0.07785888016223907
saved model at epoch 6 with error_rate value: 0.07336702197790146
saved model at epoch 7 with error_rate value: 0.0656934306025505
saved model at epoch 8 with error_rate value: 0.06400898098945618
saved model at epoch 9 with error_rate value: 0.06157589331269264
saved model at epoch 10 with error_rate value: 0.06120157241821289
```

In [69]:
```
learn.unfreeze()
```

In [70]:
```python
learn.lr_find()
learn.recorder.plot()
```

```
LR Finder is complete, type {learner_name}.recorder.plot() to see the grap
h.
```



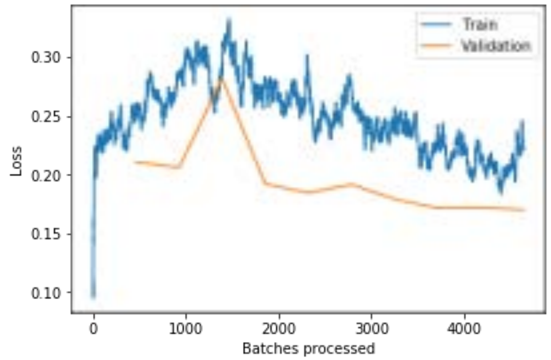
In [71]:
```python
learn.fit_one_cycle(10, max_lr=slice(3e-5, lr/5),
                    callbacks=[
                        SaveModelCallbackVerbose(learn,
                                                 monitor='error_rate',
                                                 mode='min',
                                                 name='20181206-rn50class-st
                    ]
                   )
```

Total time: 1:40:01

epoch	train_loss	valid_loss	error_rate
1	0.247885	0.210452	0.069249
2	0.283159	0.205725	0.072244
3	0.289417	0.281262	0.092083
4	0.278240	0.191837	0.068127
5	0.283583	0.184188	0.064945
6	0.276350	0.191253	0.066255
7	0.254773	0.178890	0.060266
8	0.233812	0.171120	0.061389
9	0.213923	0.171491	0.060640
10	0.221029	0.169698	0.059891

```
saved model at epoch 1 with error_rate value: 0.06924948841333389
saved model at epoch 4 with error_rate value: 0.06812652200460434
saved model at epoch 5 with error_rate value: 0.064944788813591
saved model at epoch 7 with error_rate value: 0.06026576831936836
saved model at epoch 10 with error_rate value: 0.05989144742488861
```

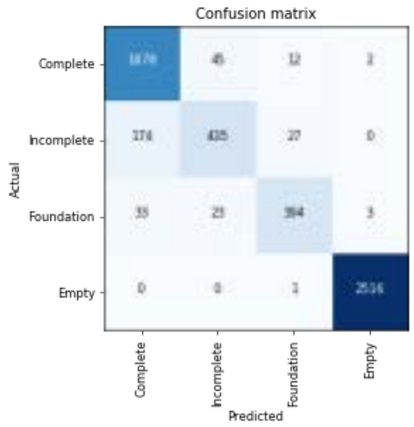
In [72]:
```python
learn.recorder.plot_losses()
```



Look at Results

In [74]:
```python
interp = ClassificationInterpretation.from_learner(learn)
```

In [76]:
```python
interp.plot_confusion_matrix(figsize=(5,5), dpi=60)
```



In [77]:
```python
interp.most_confused(min_val=2)
```

Out[77]:
```
[('Incomplete', 'Complete', 174),
 ('Complete', 'Incomplete', 45),
 ('Foundation', 'Complete', 33),
 ('Incomplete', 'Foundation', 27),
 ('Foundation', 'Incomplete', 23),
 ('Complete', 'Foundation', 12),
 ('Foundation', 'Empty', 3)]
```

In [79]:
```
interp.plot_top_losses(16, figsize=(15,11))
```

t-SNE Visualization (thanks to & adapted from @KarlH)

https://forums.fast.ai/t/share-your-work-here/27676/53 (https://forums.fast.ai/t/share-your-work-here/27676/53)

https://github.com/kheyer/ML-DL-Projects/blob/master/Pets%20TSNE/pets_tsne.ipynb (https://github.com/kheyer/ML-DL-Projects/blob/master/Pets%20TSNE/pets_tsne.ipynb)

In [80]:
```
from sklearn.manifold import TSNE
import seaborn as sns
from sklearn import manifold, datasets
from sklearn.metrics.pairwise import pairwise_distances
from sklearn.metrics import confusion_matrix
from scipy.spatial.distance import squareform
from matplotlib.offsetbox import OffsetImage, AnnotationBbox
from matplotlib.ticker import NullFormatter
import PIL
```

In [81]:
```
preds = interp.probs
y = interp.y_true
losses = interp.losses
```

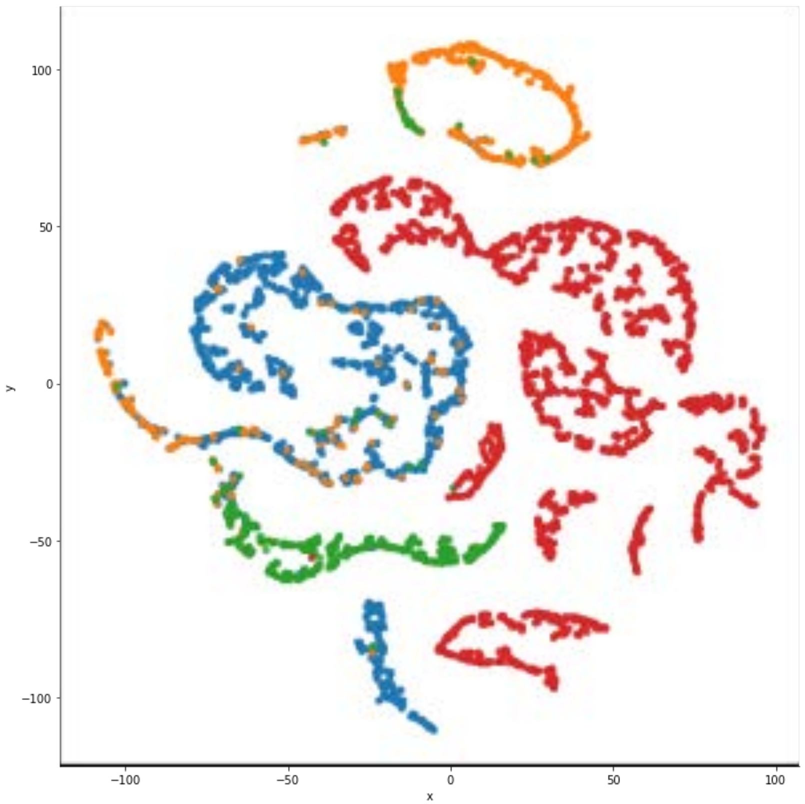
In [82]:
```
probs_trans = manifold.TSNE(n_components=2, perplexity=15).fit_transform(pre
```

In [83]:
```
prob_df = pd.DataFrame(np.concatenate((probs_trans, y[:,None]), axis=1), col
prob_df.head()
```

Out[83]:

	x	y	labels
0	56.746861	-47.716217	3.0
1	-48.950485	-3.635262	0.0
2	-5.009671	3.444134	0.0
3	3.583071	-5.047320	0.0
4	-21.317375	-26.444191	0.0

In [84]:
```
g = sns.lmplot('x', 'y', data=prob_df, hue='labels', fit_reg=False, legend=F
```



In [85]:
```
prob_df['fname'] = data.valid_ds.items
prob_df['loss'] = losses
prob_df.head()
```

Out[85]:

	x	y	labels	fname	loss
0	56.746861	-47.716217	3.0	/storage/classify-data/images/grid028_00000_Em...	-0.000000
1	-48.950485	-3.635262	0.0	/storage/classify-data/images/grid028_00001_Co...	0.003945
2	-5.009671	3.444134	0.0	/storage/classify-data/images/grid028_00002_Co...	0.046917
3	3.583071	-5.047320	0.0	/storage/classify-data/images/grid028_00003_Co...	0.048156
4	-21.317375	-26.444191	0.0	/storage/classify-data/images/grid028_00004_Co...	0.080974

In [86]:
```
# modified to optionally filter by idxs

def visualize_scatter_with_images(scaled_data, df, idxs, figsize=(64,64), in
    scaled_data = scaled_data[idxs]
    df = df.iloc[idxs]

    fig, ax = plt.subplots(figsize=figsize)
    artists = []
    xx = (scaled_data[:,0])
    yy = (scaled_data[:,1])

    for (i,x,y) in zip(idxs,xx,yy):
        im = PIL.Image.open(df['fname'][i])
        im.thumbnail((64,64))
        img = OffsetImage(im, zoom=image_zoom, cmap='gray')
        ab = AnnotationBbox(img, (x, y), xycoords='data', frameon=False)
        artists.append(ax.add_artist(ab))
    ax.update_datalim(np.column_stack([xx,yy]))
    ax.autoscale()

#    fig.savefig(f'TSNE_{suffix}.jpg', bbox_inches = 'tight')
    return fig, ax
```

In [87]:
```
fig, ax = visualize_scatter_with_images(probs_trans, prob_df, range(len(prob
plt.show()
```

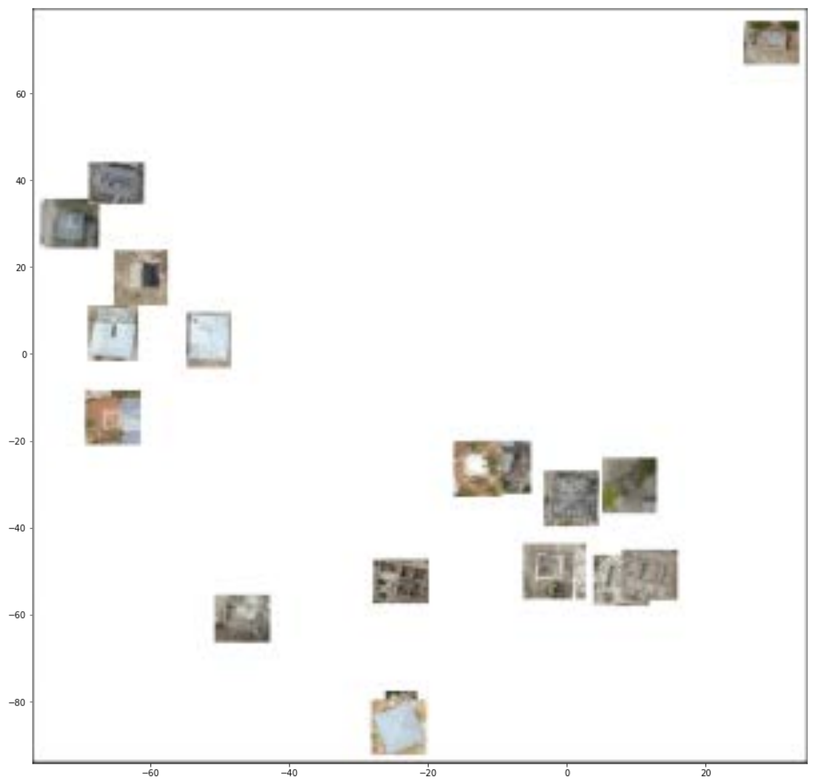
In [88]:
```
top_losses = prob_df['loss'].sort_values(ascending=False)[:20].index.values
```

In [89]:
```
prob_df.iloc[top_losses]
```

Out[89]:

	x	y	labels	fname	loss
1676	9.071122	-30.559656	2.0	/storage/classify-data/images/grid029_00218_Fo...	9.658810
2390	-23.901659	-84.158226	2.0	/storage/classify-data/images/grid029_00880_Fo...	7.988194
2236	-23.951727	-52.477448	0.0	/storage/classify-data/images/grid029_00735_Co...	7.502900
3955	-24.108377	-86.259254	1.0	/storage/classify-data/images/grid042_00397_In...	6.312711
2984	0.596981	-33.512062	0.0	/storage/classify-data/images/grid029_01434_Co...	6.264024
1449	-51.541935	3.057128	1.0	/storage/classify-data/images/grid029_00008_In...	5.652417
2847	-9.209568	-26.133133	2.0	/storage/classify-data/images/grid029_01307_Fo...	5.629231
1460	-65.345856	4.596048	1.0	/storage/classify-data/images/grid029_00018_In...	5.316871
1477	-61.389629	17.511150	1.0	/storage/classify-data/images/grid029_00033_In...	5.279524
3560	-12.731878	-26.593086	2.0	/storage/classify-data/images/grid042_00037_Fo...	5.165102
2052	7.851956	-52.302036	1.0	/storage/classify-data/images/grid029_00566_In...	4.968777
2059	11.943326	-50.991638	1.0	/storage/classify-data/images/grid029_00572_In...	4.938722
1486	-1.297820	-50.215778	1.0	/storage/classify-data/images/grid029_00041_In...	4.802966
2546	-71.905006	29.902550	1.0	/storage/classify-data/images/grid029_01027_In...	4.712808
2484	-71.327370	29.958330	1.0	/storage/classify-data/images/grid029_00969_In...	4.699991
1494	-2.534295	-50.299793	1.0	/storage/classify-data/images/grid029_00049_In...	4.557220
2032	29.490635	71.660698	2.0	/storage/classify-data/images/grid029_00547_Fo...	4.507183
1917	-64.892960	39.141045	1.0	/storage/classify-data/images/grid029_00440_In...	4.495970
4086	-65.361137	-14.892749	2.0	/storage/classify-data/images/grid042_00516_Fo...	4.469344
1542	-46.737644	-61.083656	0.0	/storage/classify-data/images/grid029_00094_Co...	4.340938

In [90]:
```
# show only images with top 20 losses
fig, ax = visualize_scatter_with_images(probs_trans, prob_df, top_losses, fi
plt.show()
```



Grad-CAM based on lesson6-pets-more

In [91]:
```
m = learn.model.eval()
```

In [92]:
```
idx = 12
x,y = data.valid_ds[idx]
x.show()
data.valid_ds.y[idx]
```

Out[92]:
```
Category Incomplete
```

In [93]:
```
xb, yb = data.one_item(x) # make batch with one item
xb_im = Image(data.denorm(xb)[0]) # denorm item into viewable image
xb = xb.cuda() # load on gpu
```

In [94]:
```
xb_im.show(), xb.shape, yb.shape
```

Out[94]:
```
(None, torch.Size([1, 3, 512, 512]), torch.Size([1]))
```

In [95]:
```
y, yb
```

Out[95]:
```
(Category Incomplete, tensor([0], device='cuda:0'))
```

In [96]:
```
from fastai.callbacks.hooks import *
import pdb
```

In [115]:
```
def hooked_backward(cat=y):
#     pdb.set_trace()
    with hook_output(m[0]) as hook_a: # set activation hook
        with hook_output(m[0], grad=True) as hook_g: # set gradient hook
            preds = m(xb) # forward pass
            preds[0,int(cat)].backward() # backward pass
    return hook_a, hook_g
```

In [116]:
```
hook_a, hook_g = hooked_backward()
```

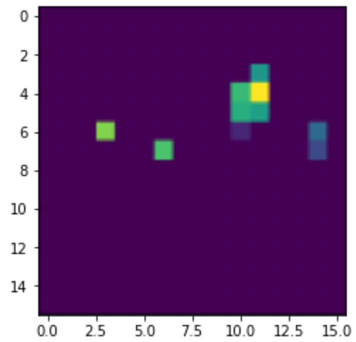
In [117]:
```
acts = hook_a.stored[0].cpu()
```

In [118]:
```
acts.shape
```

Out[118]:
```
torch.Size([2048, 16, 16])
```

In [119]:
```
plt.imshow(acts[0])
```

Out[119]:
```
<matplotlib.image.AxesImage at 0x7f5229f17630>
```

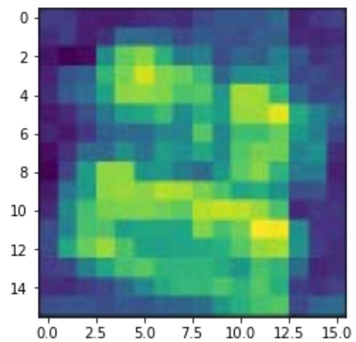


In [120]:
```
avg_acts = acts.mean(0) # get the "pixel"-wise mean of activations (avg acro
avg_acts.shape
```

Out[120]:
```
torch.Size([16, 16])
```

In [121]:
```
plt.imshow(avg_acts)
```

Out[121]:
```
<matplotlib.image.AxesImage at 0x7f5229e7f080>
```



In [122]:
```
grad = hook_g.stored[0][0].cpu()
```

In [123]:
```
grad.shape
```

Out[123]:
```
torch.Size([2048, 16, 16])
```

In [124]:
```
grad_chan = grad.mean(1).mean(1) # get the avg of grads for each channel
grad.shape, grad_chan.shape
```

Out[124]: (torch.Size([2048, 16, 16]), torch.Size([2048]))

In [125]:
```
grad_chan[...,None,None].shape # make 2 more axes to be same shape as acts
```

Out[125]: torch.Size([2048, 1, 1])

In [126]:
```
(acts*grad_chan[...,None,None]).mean(0).shape
```

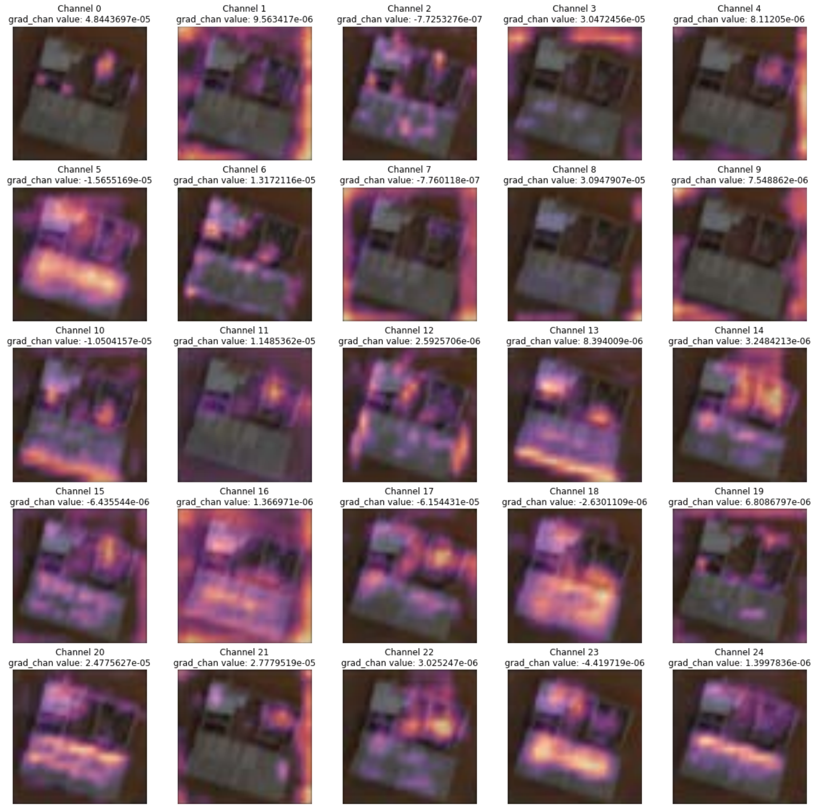
Out[126]: torch.Size([16, 16])

In [127]:
```
mult = (acts*grad_chan[...,None,None]).mean(0)
```

In [129]:
```
def show_heatmap(hm,interpol='bilinear',cmap='magma'):
    _, ax = plt.subplots()
    xb_im.show(ax)
    ax.imshow(hm, alpha=0.6, extent=(0,512,512,0), interpolation=interpol,cm
```

In [130]:
```
show_heatmap(mult)
```

In [134]:
```
fig, axes = plt.subplots(5,5, figsize=(20,20))
for j, ax in enumerate(axes.flat):
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)
    xb_im.show(ax=ax)
    ax.set_title('Channel '+str(j)+ '\n'+'grad_chan value: '+str(grad_chan.r
    ax.imshow(acts[j], alpha=0.6, extent=(0,512,512,0), interpolation='bilir
#     ax.imshow([importance_idxs[j]]), alpha=0.6)
plt.show()
```



In [135]:
```
# thanks @henripal, from https://github.com/henripal/maps/blob/master/nbs/bi
import scipy.ndimage

def upsample(heatmap, zoom=32):
    upsampled = scipy.ndimage.zoom(heatmap, zoom)
    upsampled = (upsampled - np.min(upsampled))/((np.max(upsampled) - np.mir
    return upsampled
```

In [136]:
```
grad_df = pd.DataFrame(grad_chan.numpy(), columns=['grad_chan'])
grad_df.head()
```

Out[136]:

	grad_chan
0	4.844370e-05
1	9.563417e-06
2	-7.725328e-07
3	3.047246e-05
4	8.112050e-06

In [137]:
```
importance_idxs = grad_df.sort_values(by='grad_chan',ascending=False).index.
importance_idxs
```

Out[137]:
```
array([ 101,  220, 1270,  631, ...,   74,  844, 1954,  660])
```

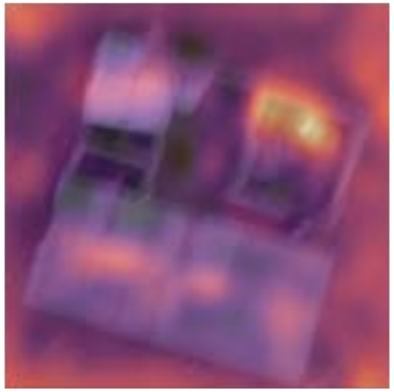
In [138]:
```
grad_df.iloc[importance_idxs].head()
```

Out[138]:

	grad_chan
101	0.005839
220	0.003543
1270	0.002052
631	0.001911
1813	0.001636

In [143]:
```
# heatmap with most important 100 activations (ranked by grad_chan)
fm_up = [upsample(fm) for fm in acts[importance_idxs[:100]]]
xb_im.show(figsize=(5,5))
plt.imshow(np.mean(fm_up, axis=0),alpha=0.6, cmap='magma')
```

Out[143]:
```
<matplotlib.image.AxesImage at 0x7f52295b50b8>
```



In [144]:
```
# heatmap with least important 100 activations (ranked by grad_chan)
fm_up = [upsample(fm) for fm in acts[importance_idxs[-100:]]]
xb_im.show(figsize=(5,5))
plt.imshow(np.mean(fm_up, axis=0),alpha=0.6, cmap='magma')
```

Out[144]:
```
<matplotlib.image.AxesImage at 0x7f5229579940>
```

Test time

In [145]:
```
data.export()
```

In [146]:
```
empty_data = ImageDataBunch.load_empty(path, tfms=tfms, size=512).normalize(
learn = create_cnn(empty_data, models.resnet50)
```

In [147]:
```
empty_data.classes
```

Out[147]:
```
['Complete', 'Incomplete', 'Foundation', 'Empty']
```

In [148]:
```python
learn.load('20181206-rn50class-stage2-best')
learn.model.eval()
```

Out[148]:
```
Sequential(
  (0): Sequential(
    (0): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3,
3), bias=False)
    (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_run
ning_stats=True)
    (2): ReLU(inplace)
    (3): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_
mode=False)
    (4): Sequential(
      (0): Bottleneck(
        (conv1): Conv2d(64, 64, kernel_size=(1, 1), stride=(1, 1), bias=
False)
        (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
        (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), paddi
ng=(1, 1), bias=False)
        (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, tra
ck_running_stats=True)
```

In [149]:
```python
grid_num = '119'
test_path = Path(f'/storage/znz-classify-001/demo_test/test_{grid_num}')
test_fns = [o for o in sorted(test_path.iterdir()) if '.jpg' in o.name]
print(len(test_fns))
```

```
13552
```

In [161]:
```python
img = open_image(test_fns[100])
img.show()
plt.show()
```

In [162]:
```python
img = img.apply_tfms(tfms[1],resize_method=ResizeMethod.SQUISH, size=512, bs
img.show()
```

In [165]:
```python
learn.predict(img)
```

Out[165]:
```
(Category Complete,
 tensor(0),
 tensor([9.6798e-01, 3.0493e-02, 1.4308e-03, 9.5591e-05]))
```

In [152]:
```python
from tqdm import tqdm
```

In [154]:
```python
preds = []
pred_classes = []
for fn in tqdm(test_fns[:100]):
    try:
        img = open_image(fn)
        img = img.apply_tfms(tfms[1],resize_method=ResizeMethod.SQUISH, size
        pred_class,pred_idx,outputs = learn.predict(img)
        preds.append(list(to_np(outputs)))
        pred_classes.append(pred_class)
    except Exception as exc:
        print(f'{exc}')
        preds.append([-1,-1,-1,-1])
        pred_classes.append('error')
```

```
100%|██████████| 100/100 [00:04<00:00, 20.55it/s]
```

In [155]:
```python
img.show()
```

In [156]:
```python
np.round(preds,2)
```

Out[156]:
```
array([[0.99, 0.01, 0.  , 0.  ],
       [0.99, 0.01, 0.  , 0.  ],
       [0.51, 0.49, 0.  , 0.  ],
       [0.17, 0.04, 0.79, 0.  ],
       ...,
       [1.  , 0.  , 0.  , 0.  ],
       [0.97, 0.01, 0.  , 0.02],
       [0.95, 0.04, 0.  , 0.  ],
       [0.33, 0.66, 0.01, 0.  ]], dtype=float32)
```

In [157]:
```python
np.round(preds,2)
```

Out[157]:
```
array([[0.99, 0.01, 0.  , 0.  ],
       [0.99, 0.01, 0.  , 0.  ],
       [0.51, 0.49, 0.  , 0.  ],
       [0.17, 0.04, 0.79, 0.  ],
       ...,
       [1.  , 0.  , 0.  , 0.  ],
       [0.97, 0.01, 0.  , 0.02],
       [0.95, 0.04, 0.  , 0.  ],
       [0.33, 0.66, 0.01, 0.  ]], dtype=float32)
```

In [158]:
```python
df = pd.DataFrame(data=preds, columns=data.classes)
df['fname'] = [o.name for o in test_fns[:len(preds)]]
df['predicted_class'] = pred_classes
```

In [159]:
```python
df.head()
```

Out[159]:

	Complete	Incomplete	Foundation	Empty	fname	predicted_class
0	0.985044	0.013088	0.001585	0.000283	119_00000_test.jpg	Complete
1	0.986397	0.013174	0.000414	0.000015	119_00001_test.jpg	Complete
2	0.506189	0.490988	0.002788	0.000035	119_00002_test.jpg	Complete
3	0.166216	0.043905	0.789644	0.000234	119_00003_test.jpg	Foundation
4	0.953893	0.045666	0.000435	0.000005	119_00004_test.jpg	Complete

In [160]:
```python
for i in range(10):
    img = open_image(test_path/df.iloc[i]['fname'])
    print(df.iloc[i]['predicted_class'], df.iloc[i][df.iloc[i]['predicted_cl
    img.show()
    plt.show()
```

Complete 0.9850437641143799

Complete 0.9863974452018738

Complete 0.5061893463134766

Foundation 0.789644181728363

Complete 0.9538934826850891

```
Foundation 0.9689040780067444
```

```
Complete 0.9510454535484314
```

```
Incomplete 0.5464768409729004
```

```
Complete 0.586933970451355
```

```
Complete 0.9919455647468567
```

In [220]:
```
df.to_csv('preds.csv',index=False)
```