This Project Was a Mistake: Tactical Errors in a Protocol for Aleppo's Reconstruction

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This project is a protocol for the reconstruction of Aleppo, Syria. We aim to investigate the impact machine intelligence has on the relationship between the architect, the designed output, and the people who will use it. The politically charged nature of the site allows us to marry an understanding of "participatory" and "autonomous" design with necessary considerations for preservation, memory, and local culture. We believe this context allows us to explore a fundamental characteristic of architecture in the era of machine intelligence: our relationship, as designers, to error.

Historically, post-war responses in cities like Berlin and Sarajevo have attempted to "exactly rebuild." We echo the theories of Lebbeus Woods in response: reconstruction efforts in a post-war environment cannot and should not attempt to exactly replicate the pre-war condition.[1] The trauma of war can only be healed through remembrance. The character of the site has been forever changed by the destruction of war, but its memory persists as data. This leaves us with two questions:

What is the role of the architect in an inherently bottom-up process of reconstruction?

If cultural memory exists as information, then how can that data be leveraged for both preservation and design?

Our project answers these questions by proposing of a new form of preservation through an automated and participatory

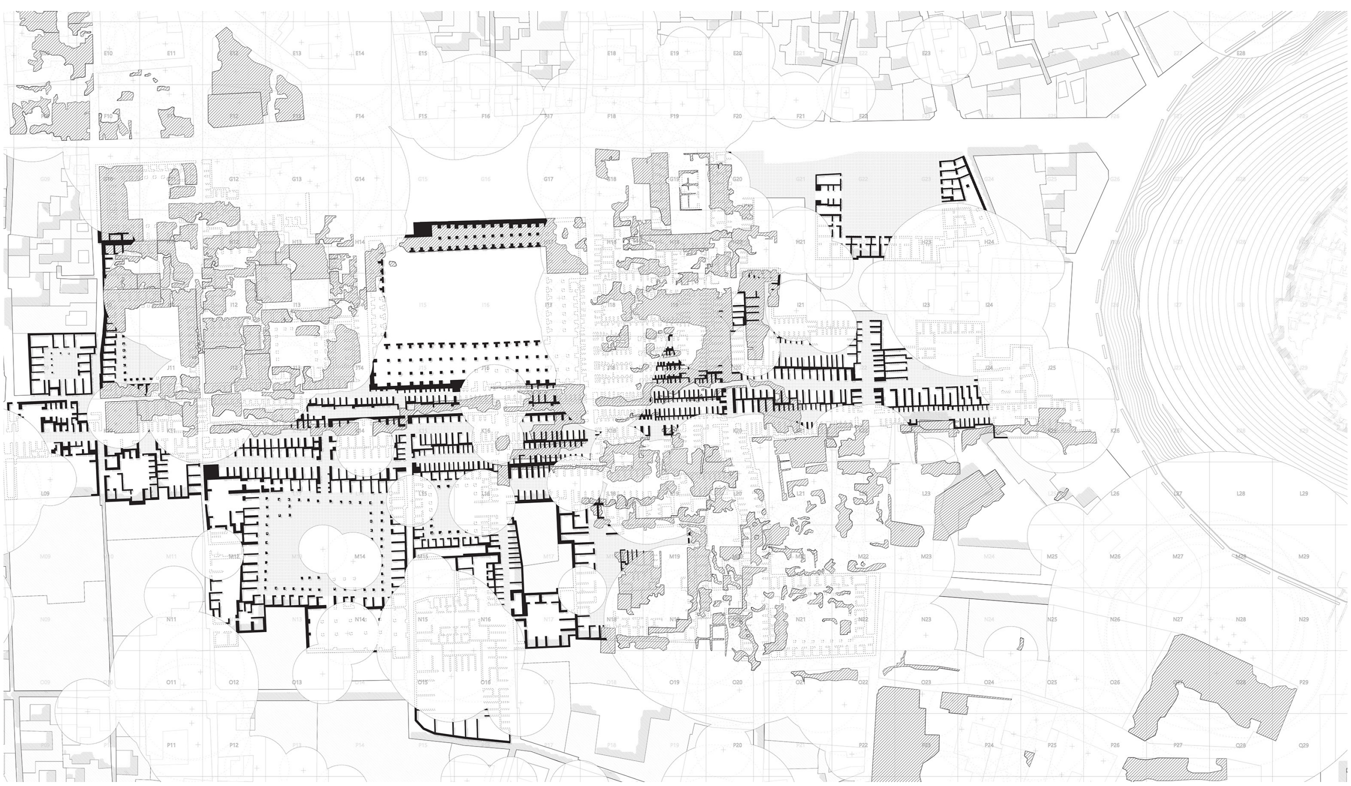

Figure 1. A mapping of wartime destruction in and around the Old Medina of Aleppo, Syria.

Figure 2. An exquisite corpse of cultural motifs of Aleppo. Adam Elstein.

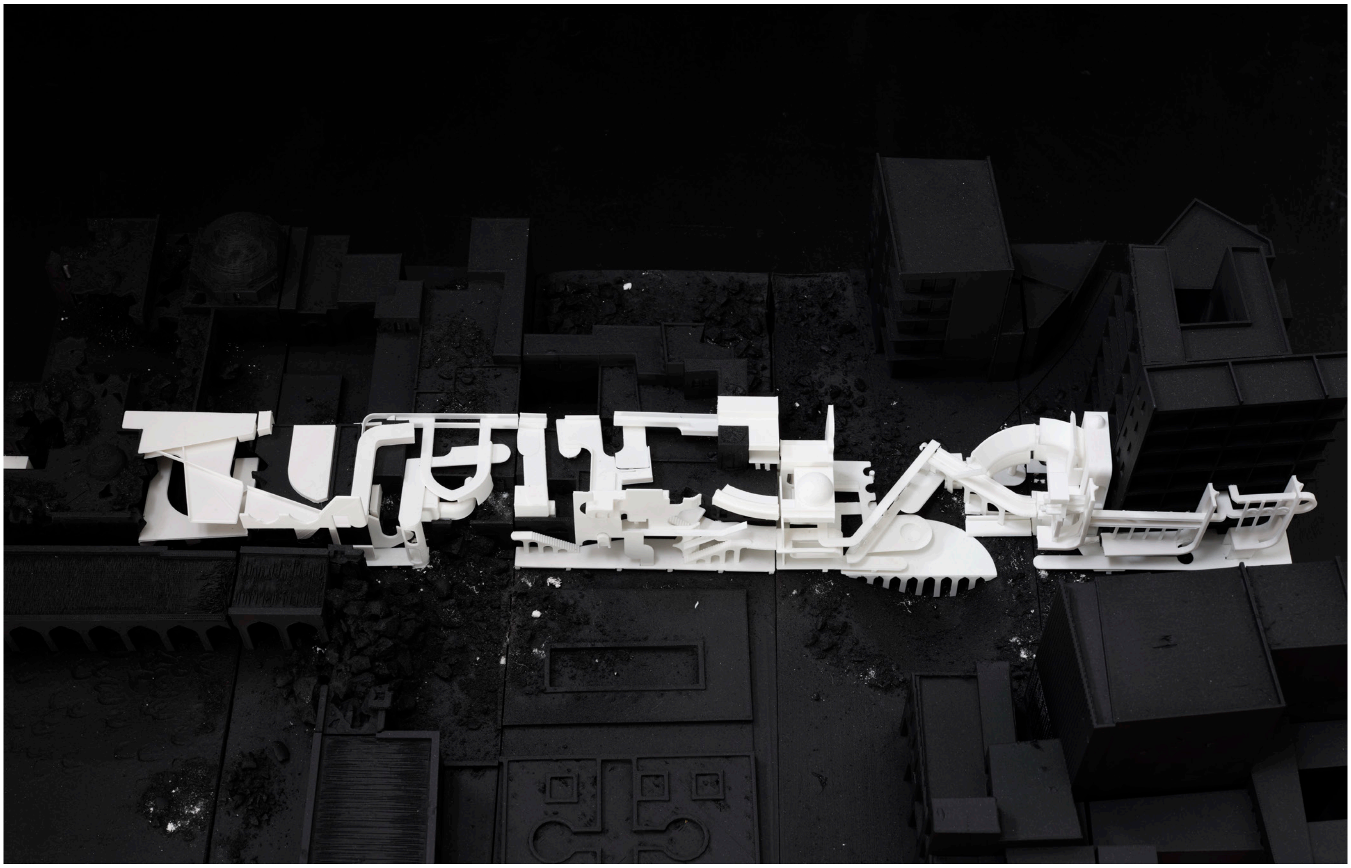

Figure 3. Serial reconstruction of the area around the Great Umayyad Mosque. Adam Elstein.

reconstruction of Aleppo. Our constraints revolve around coordinating a set of instructions and interactions. Top-down intentions to restore a pre-war order conflict with bottom-up desires for novel reconstruction. As a result, we understand our project as a protocol instead of a final a determined proposal. The game is then to outline a class of potentials and possibilities -- not propose what literally gets built. In our simulation of this future Aleppo, citizens are asked to photograph and submit images of sites that they would like to reconstruct to a data set leveraged by us, the designers. Bottom-up documentation is like voting. But how are we to know what they want us to see? What they are trying to say with these depictions of their trauma?[2] And, even ***if*** that was knowable, how are we to resolve the piles of conflicting images for the future of Aleppo?[3] This opinionated data needs a judge.

We turned to a machine learning algorithm called a generative adversarial network (GAN). A recent advancement in computer intelligence, GANs can be "taught" certain qualitative concepts by being "fed" large collections of examples (often these are images). They can then be asked to independently create (generate) an example. This process, called training, often leads to simultaneously surprising ***and*** convincing versions of the given concept. And, as designers without the proper maths or computer science background to be waving this weapon around, we fixated on the tool because of its ***adversarial*** nature. A GAN is made up of two primary actors: a discriminator and a generator. The discriminator, as the name implies, must decide whether the images created by the generator "belong" to the original data set. Each round measures how "correct" the two combatants were in their determinations, and then they react (learn).[4] Ideally, in the end, you're left with a generator than can ***independently*** create believable instances of the data set's subject. This understanding is an implicit synthesis of the qualities in that data. The GAN did not, and does not, know how to describe the data the way your or I might. But it feels like it can.

We taught a GAN about several cultural motifs of Aleppo (e.g. the dome, the arch, and the minaret).[5] Aleppo, at the time of writing, is not accessible. Our data set consisted of images scraped from the web. But where the machine is trained on a pre-war ideal, its results must be deployed onto a post-war reality. Errors arise from the collision of these two categorically distinct data sets. This led us to our primary conclusion: the possibility for error, whether from the machine or the human input, is a critical and productive constraint.[6] The output was then taken as literal sectional instructions. Our interpretations of the machine learning output accumulated into a pile

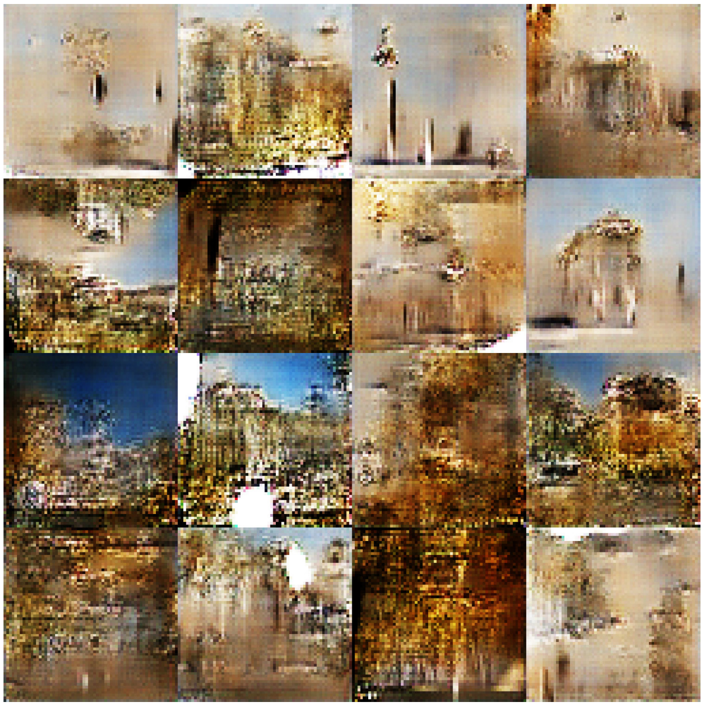

Figure 4. Raw output of a GAN trained on mosque domes.

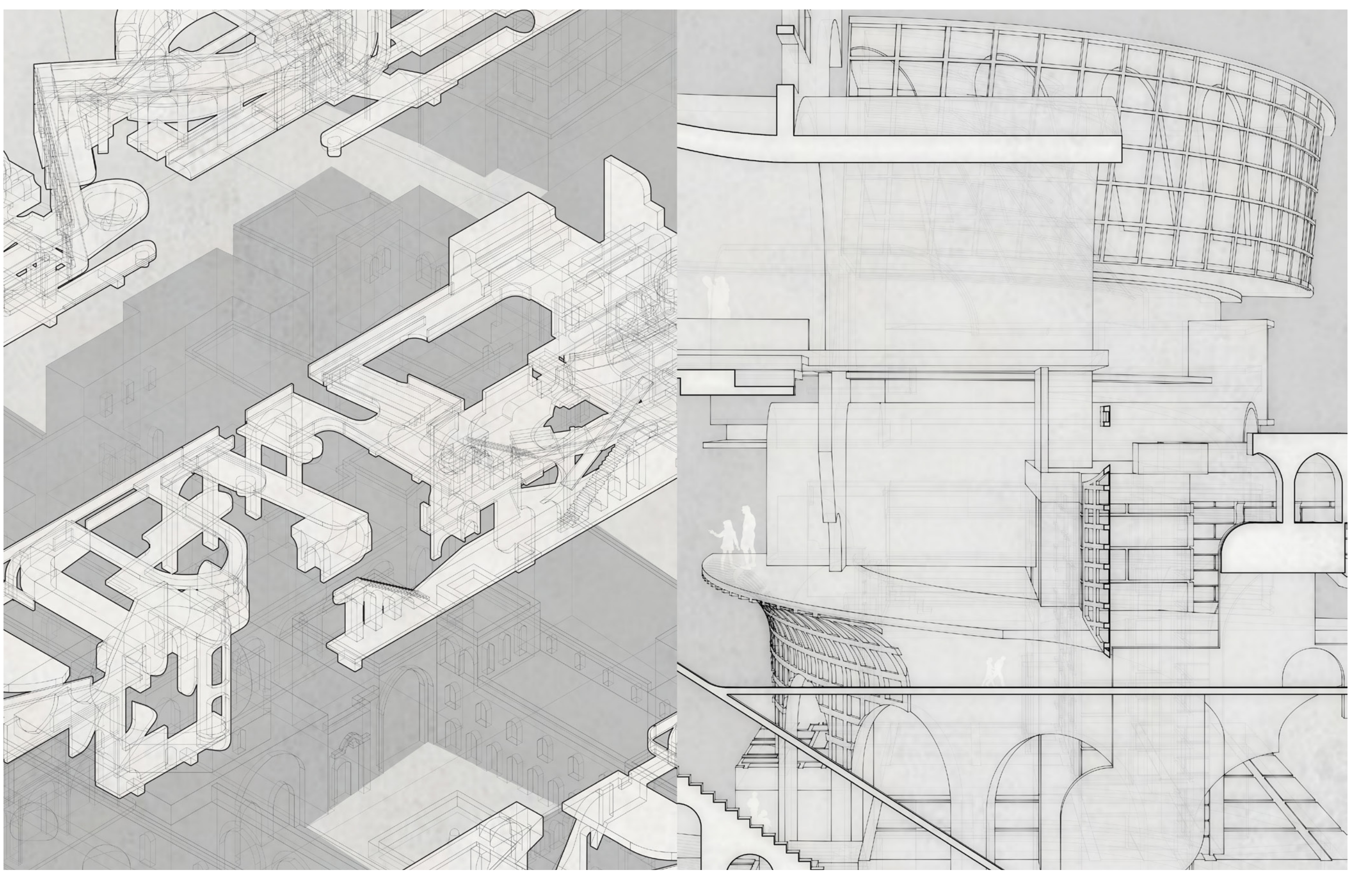

Figure 5. Architectural representation of one simulated result.

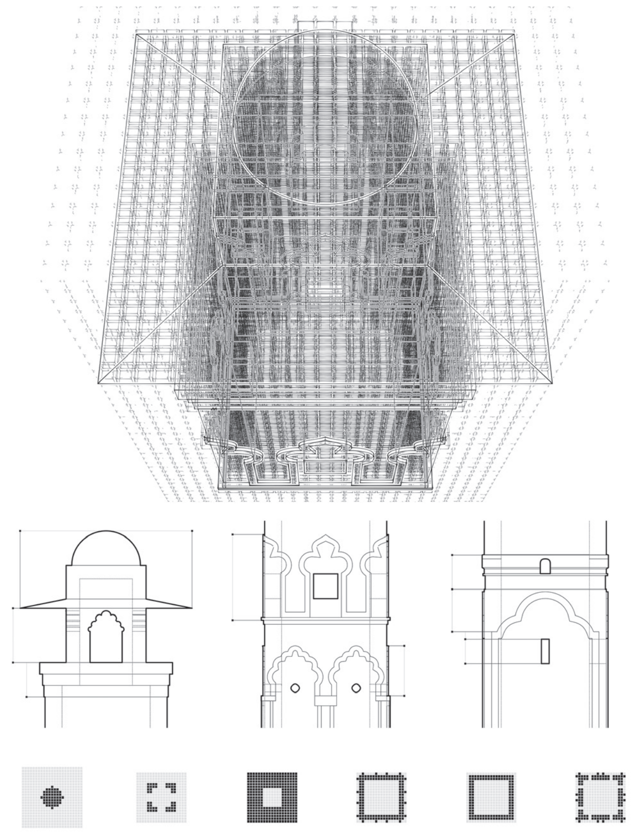

Figure 6. Analysis of a minaret.

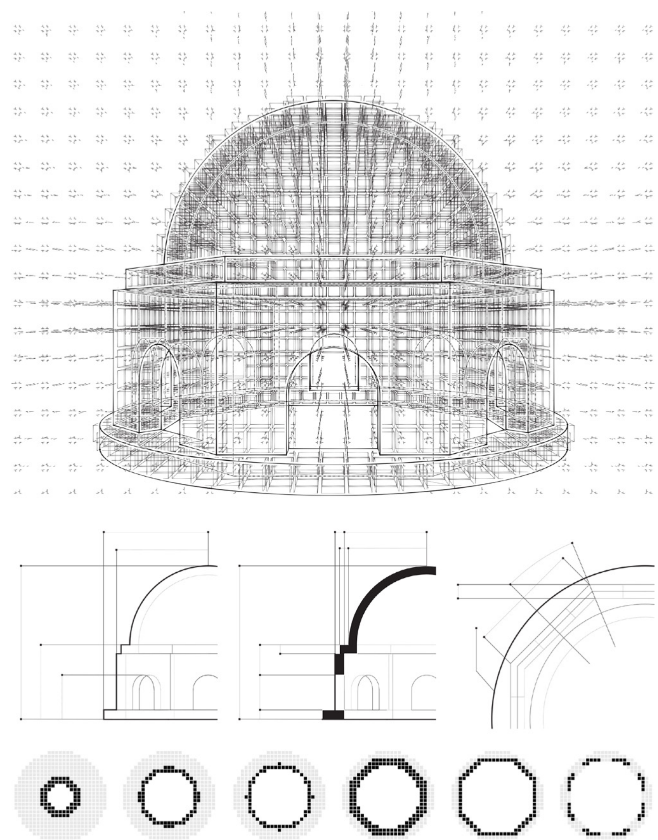

Figure 7. Analysis of a mosque dome.

of mistakes: misreadings by the machine, our misreadings of misreadings by the machine, and so on.

The project leans too heavily on speculation and simulation to make a serious claim about the literal implementation or physical deployment of machine learning algorithms into the built environment. We do not address some simple, critical questions. What is all this digital putty actually made of, in the end? Who's doing all this building? But we ***would l***ike to weight in on the question of our intangible relationship with error via the two earlier questions.

What is the role of the architect in the context of reconstruction? They are the designer of ***protocol*** for the interaction of their top-down automated systems and bottom-up pool of participants.

How do we use data? It is a wellspring of error and a tool for implicit synthesis of its conclusions.

This work was started as an undergraduate degree project at Pratt Institute. We would like to express our gratitude to our three critics, Adam Dayem (for some incredible photography), Michele Gorman (for the faith in worldbuilding), and Ashley Simone (for stopping us from saying stupid things). Their contributions are, of course, far beyond what we could put in so few words here.

ENDNOTES

1. Lebbeus Woods, *Radical Reconstruction* (Princeton Architectural Press, 2001)
2. Judith Butler, *Frames of War: When Is Life Grievable?* (Brooklyn: Verso, 2009)
3. Christopher Alexander, *Notes on the Synthesis of Form* (Harver University Press, 1964)
4. Alec Radford, Luke Metz, Soumith Chintala, "Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks," in *4th International Conference on Learning Representations,* ed. Yoshua Bengio, Yann LeCun (San Juan: ICLR, 2016)
5. Taehoon Kim, "DCGAN-tensorflow" https://github.com/carpedm20/DCGAN-tensorflow.
6. Asli Serbest, Mona Mahall, "Theory of the Impossibility of a Theory of Error," in *Perspecta 46: Error,* ed. Joseph Clarke, Emma Jane Bloomfield (Yale, 2013)
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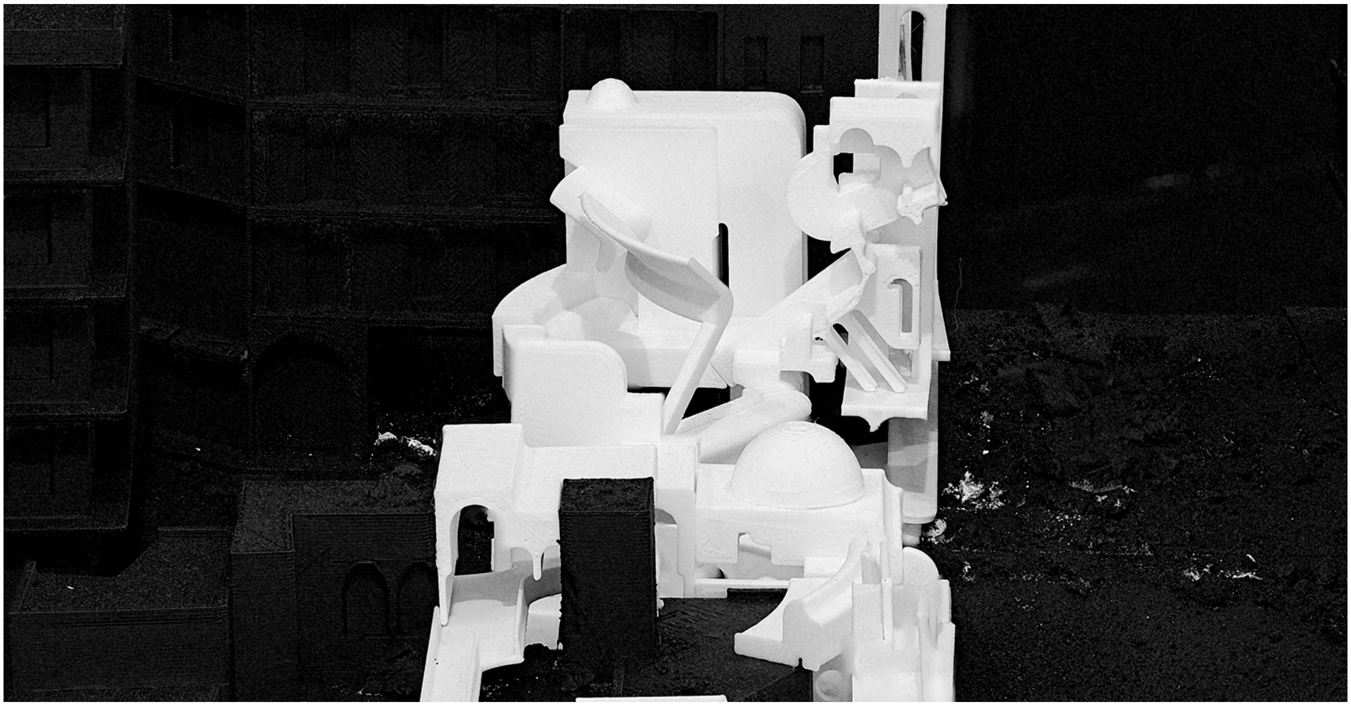

Figure 8. Armature grafted onto destroyed housing. Adam Elstein.

Figure 9. Circulation clashing with surviving conditions of the site.